MODELLING COMPRESSIVE STRENGTH OF CONCRETE FROM NON-DESTRUCTIVE TESTS USING MACHINE LEARNING

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ABSTRACT

Concrete is the most widely used structural material for construction today. Traditionally, concrete has been fabricated from a few well-defined components: Cement, water, fine aggregate, coarse aggregate, etc. In concrete mix design and quality control, the compressive strength of concrete is regarded as the most important property.

The main objective is to model the compressive strength of concrete obtained from non-destructive test using machine learning. The specific objectives are to narrow down the search to factors that significantly contribute to the compressive strength of concrete, to compare results from destructive methods with non-destructive methods and to create a model using the factors to be considered.

Linear regression has successfully been used as a sanity check. The most successful non-NN algorithm, stepwise quadratic regression with interactions was also featured. The repeatability of the results is also a matter of interest since the neural network also changes rapidly even without changing the neural network parameters.

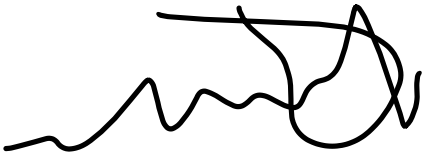
The neural network, when tweaked, was also able to give a performance better than the other methods. It was demonstrated that neural networks could give results better than other methods could.

Nevertheless, the investigation also made known that more data would be appreciated, especially outside of the 10-45MPa range.

A model for the compressive strength of concrete from non-destructive test using machine learning has been obtained. The model is a neural network that contains only the more influential variables. This model could be seen on subsection 5.5.3.2 (page 157). This model (tweak neural network) is the best due to the higher R-squared compared to the other models. The best model contains 21 inputs with a hidden layer of size 1 to produce 1 output. This model has an R-squared of 0.9773.

More data is recommended to be gathered. The analysis could be augmented if there is more data.

More factors could be considered. The only non-destructive factor that was used in the analysis was rebound number and ultrasonic pulse velocity. Other factors such as Leeb hardness, electrical resistivity, and point load index would still need a greater foray into the current research.



Daniel Kenneth Villanueva

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Chapter I

Problem Setting

1.1 Background of the Study

1.1.1 Historical background

Concrete is the most widely used structural material for construction today. Traditionally, concrete has been fabricated from a few well-defined components: Cement, water, fine aggregate, coarse aggregate, etc. In concrete mix design and quality control, the compressive strength of concrete is regarded as the most important property. Many other properties of concrete, such as elastic modulus, water tightness or impermeability, resistance to weathering agents, etc. are directly related to the strength. The compressive strength of concrete is many times greater than other types of strength, and a majority of concrete elements are designed to take advantage of the higher compressive strength of the material. Most often, an ultimate target in the mixture design is the 28th day compressive strength. The 28th day compressive strength is usually determined based on a standard uniaxial compression test and is accepted universally as a general index of concrete strength. The compressive strength of concrete is related to mix proportions and mix preparation techniques, but the result of the compression test of a specimen can be influenced by the shape, dimension, and the boundary conditions of the specimen. Traditionally, concrete mix is designed based on previous

experiences. However, knowledge from previous experiences is limited since all possible combinations of components, proportions, and mixing techniques have not been investigated or published. (J.-I. Kim et al., 2004)

Durability performance of concrete structures is unfortunately not always as good as anticipated for a variety of reasons. The principal driving force for the numerous developments of non-destructive test methods and equipment has been the requirement of industry worldwide for long-term maintenance strategies. There have been significant advances in equipment capabilities and a range of new techniques related to durability and integrity assessment. These techniques have become established in practice. The troubleshooting and maintenance role of in situ testing remains assured. However, attitudes amongst the engineering community towards in-place testing for quality control during construction remain largely unchanged. This is apart from limited acceptance of testing for strength development monitoring and increased use of covermeters. Cubes/cylinders remain the ‘gold standard’ for concrete acceptance for the foreseeable future. (Maierhofer et al., 2010)

In 1974, several high-alumina-cement pre-tensioned beams in the UK collapsed because of major loss of concrete strength owing to the ‘conversion’ of the high-alumina-cement concrete under unfavorable environmental

conditions. This led to a nationwide program of inspection and assessment. (Maierhofer et al., 2010)

What is intended to be done with regards to non-destructive testing and compressive strength is to look at the different factors that could affect the compressive strength of the concrete. The methods for non-destructive testing include the Rebound Hammer (RH) Test and Ultrasonic Pulse Velocity (UPV) Test.

Non-destructive testing is a kind of testing that preserves the integrity of the section being analyzed. This is useful since it allows for the concrete strength initially planned to be compared with the current concrete strength. This is useful since the strength of the concrete may not be as promised or would have degraded over time due to environmental factors. (Maierhofer et al., 2010)

Non-destructive testing is a technique that allows the investigation of the properties of concrete without needing to damage it.

Non-destructive testing is not much used in the Philippines. However, Dr. Ongpeng tested concrete beams using Portable Ultrasonic Non-destructive Digital Indicating Tester, known as PUNDIT. Testing has found that UPV result at the early age of concrete is not correlated with the 28 day compressive strength of concrete. (Ongpeng, 2015)

Non-destructive testing also has a problem with regards to the guideline

calculations given by the manufacturer. The guideline equation for the use of different non-destructive testing instruments have proven to be inadequate. This is since the conditions of the concrete used in the industry could be different from how the manufacturer have created the concretes used for testing.

Despite the major efforts in producing the British and European Standards, there are notable gaps, especially relating to reinforcement corrosion assessment. (Maierhofer et al., 2010)

A motivation for modelling the concrete strength comes from the fact that there is much disparity with regards to results from different literature. The figure below shows a part of the discrepancy.

The concept of modelling the compressive strength comes from the utopic vision that if all the factors are considered, then it would be possible to narrow down the causes for the discrepancies in the curves.

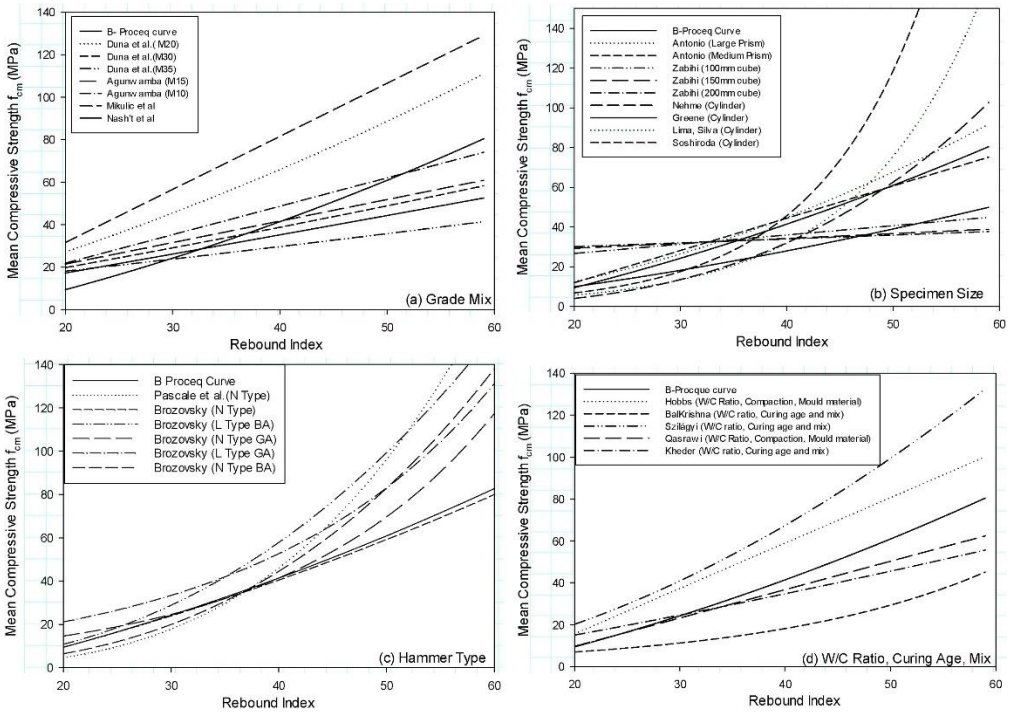


Figure 1.1.1 Rebound index vs. compressive strength relationship curves proposed by different authors considering influencing factors. (Kumavat et al., 2021)

1.1.2 Past research related to the study

Visual testing is probably the most important of all non-destructive tests. It can often provide valuable information to the well-trained eye. Visual features may be related to workmanship, structural serviceability, and material deterioration and it is particularly important that the engineer is able to differentiate between the various signs of distress which may be encountered. These include for instance, cracks, pop-outs, spalling, disintegration, color change, weathering, staining, surface blemishes and lack of uniformity.

Extensive information can be gathered from visual inspection to give a preliminary indication of the condition of the structure and allow formulation of a subsequent testing program. The visual inspection however should not be confined only to the structure being investigated. It should also include neighboring structures, the surrounding environment, and the climatic condition. This is probably the most difficult aspect of the whole structural investigation or any diagnostic works since what appears obvious to one may not be so to another.

The importance and benefits of a visual survey should not be underrated. Often the omission of what appears to be insignificant evidence can lead to a wrong conclusion being made. The advantage of a trained eye is best described by Sherlock Holmes when he wrote: *"I see no more than you, but I have trained myself to notice what I see."* (No, 2002)

(J.-I. Kim et al., 2004) has applied the practice of using neural networks with regards to destructive methods. The current study aims to do things differently by focusing on the non-destructive methods.

1.1.3 Theoretical issues of the study

The study could theoretically have a problem with regards to which parameters should be included even with tools such as principal component analysis. This stems from the fact that aside from parameters such as mux design and the age of concrete, the other factors are sparingly found.

Considering that Machine learning needs lots of data, there could be a possibility that even with the vast amount of literature, the data would still not be enough. Machine learning needs lots of data since machine learning uses a lot of variables to create the model.

The gap from past studies is with regards to the fact that the influencing factors are generally analyzed in isolation. This study aims to improve on the literature with regards to how different factors intermingle by creating a model. This would ideally be able to give insight as to the interaction of the concrete. The study also expands on the literature using ANN. The study uses MATLAB and its characteristics to create a model using ANN. The model would also be compared with regards to other models to ensure that using ANN would be helpful and to demonstrate the utility of ANN against other model types, when the other model types have not been meticulously tweaked.

1.2 Problem Statement

What is intended to be done with regards to non-destructive testing and compressive strength is to look at the different factors that could affect the compressive strength of the concrete. This has been realized in the project by looking at how the properties such as amount of cement, fine and coarse aggregates used, and water content would affect the compressive strength of the concrete. The Primary component analysis was also used to help in the search for the most effective variables. The linear

regression is also used to contribute to this search. The dataset was also segregated to those with NDT methods and those without to test the difference between including the methods and not including them. The data is processed by ANN to find the best model to predict the compressive strength. This would be important to give generality to this research. These all would therefore give insight into the different factors of concrete compressive strength.

The input parameters that would be considered include: The concrete mix design, water-cement ratio, concrete age, rebound hammer and ultrasonic pulse velocity. Additonal factors that could affect are: Compaction used, Type of Aggregate used, Carbonation depth, Curing Condition and Moisture condition. (Kumavat et al., 2021) The output parameter would be the compressive strength of concrete.

The problem has been the inconsistency with regards to the different curve fitting results that an ultrasonic pulse velocity (UPV) test and rebound hammer test would give, namely the correlation between the pulse velocity and the rebound number with the compressive strength of the concrete, which is caused by the differences in the concrete used for calibration and the concrete used in the field (Kolaiti & Papadopoulos, 1993). This study aims to solve the problem by looking at different things that were done in performing the experiment and see how the difference in the conditions of the concrete influenced the

compressive strength of concrete.

1.3 Objectives:

1.3.1 Main Objective

To model the compressive strength of concrete obtained from non-destructive test using machine learning.

1.3.2 Specific Objectives

To narrow down the search to factors that significantly contribute to the compressive strength of concrete.

To compare results from destructive methods with non-destructive methods.

Create a model using the factors to be considered.

1.4 Hypothesis of the Study

The study was able to create a model to help with the non-destructive testing of concrete.

The study was able to identify useful criteria in finding the

compressive strength of concrete.

1.5 Scope, Limitations, & Delimitations

The scope of the test would be the non-destructive methods in finding out the compressive strength of the concrete.

The limitation would be with regards to the year of data obtainable. Although limited amounts of NDT are done in the 1930s, but the first disaster that would show NDT's necessity was in 1974, with the collapse of several high-alumina-cement pre-tensioned beams.(Maierhofer et al., 2010) Another consideration would be that many research papers are normally off-access, even with the multiple subscriptions acquired by DLSU. Although Sci-Hub allows access to most of the off-limits papers, their archives would be incomplete.

The delimitation is that the study will not focus on the destructive methods for testing concrete.

1.6 Assumptions

The study will assume that the concrete from other studies is prepared correctly, and that the data analysis is correct. The study also assumes that the code inside MATLAB is correct and corresponds to

the correct algorithms. For example, it is assumed that the enabling Levenberg-Marquardt algorithm in the neural network fitting tool would make the weights and biases be updated with the correct implementation of Levenberg-Marquardt algorithm.

1.7 Significance of the Study

The study would give insight as to what factors are the most significant when it comes to determining the compressive strength of the concrete.

Moreover, the study considers the different factors that influences the done concrete tests.

Looking at the different influencing factors is important since it allows us to have a better understanding of what initial factors influence the compressive strength of the concrete.

Furthermore, the inclusion of NDT in this study has its benefits. Using NDT allows us to use concrete specimen that have already been built and put to its proper use as one of the ways to predict compressive strength. This would be important since the values of NDT would allow us to measure how concrete stands up to the test of time.(Breysse, 2012)

Chapter II

Review of Related Literature

2.1 Reinforced Concrete

2.1.1 What is concrete?

Concrete is a mixture of aggregates and paste. Aggregates typically include sand and gravel or crushed stone. The paste in here typically refers to the combination of water and Portland Cement (Gagg, 2014). Concrete is also a widely used material in the world. (Crow, 2008)

Cement is a generic term that refers to all the binder materials for a concrete (Gagg, 2014).

2.1.2 What is reinforced concrete?

Reinforced concrete consists of concrete and reinforcing bars. The reinforcing bars compensate for the fact that the concrete is weak in tension while strong in compression. (Condit, 1968)

2.1.3 Why use reinforced concrete?

Reinforced concrete is better than wood in terms of fire safety, sound insulation and acoustics, horizontal and vertical stability, and durability.(Hemström et al., 2011)

Reinforced concrete structures are also marginally more efficient in terms of limiting their CO2 emission when compared to structural steel. Moreover, Reinforced Concrete frames are also more efficient in terms of their energy consumption when compared to structural steel.(Ranjbar et al., 2021)

A counterargument, however, is with regards to the weaker inherent resistance of reinforced concrete with regards to earthquake loads. A wooden structure can withstand significant earthquakes loads without a need for a special consideration for earthquakes. Wood can deform more easily, and the light weight of the wood reduces the seismic forces inflicted to the building. This weakness could be fixed through the special design of reinforced concrete structures to withstand the earthquake loads.(Alih & Vafaei, 2019)

2.2 Compressive strength of concrete

2.2.1 Importance of compressive strength of concrete

Compressive strength is important because it is the strongest property of a concrete. The compressive strength of concrete is approximately 10 to 15% of its tensile and flexural strength respectively. The fact that the concrete strength is related to the structure of the hydrated cement paste makes it a marker of concrete quality. For the reasons stated, compressive strength is used as a measure for the serviceability and strength of concrete structures and members.(Vu et

al., 2020)

2.2.2 Factors affecting compressive strength

The factors affecting compressive strength are: concrete mix design, water-cement ratio, concrete age, rebound hammer and ultrasonic pulse velocity. Additonal factors that could affect are: Compaction used, Type of Aggregate used, Carbonation depth, Curing Condition and Moisture condition (Kumavat et al., 2021).

Effect of substituting aggregates with recycled concrete aggregate with a same mix design has no difference in compressive strength (Latif Al-Mufti & Fried, 2012). Addition of rubber as aggregate has also been considered (Albano et al., 2005).

2.3 Machine Learning

2.3.1 Usefulness of regression

Regression is used to understand the relationships between different variables. Regression is used to find the causal effect between variables. Regression is useful for finding the effects of various changes. (Sykes, n.d.) For this paper, regression is used to find the correlation between different factors and the compressive strength of concrete.

2.3.2 Different regression types

Linear regression is a way to model the relationship between a

scalar response and the exploratory variables. If there is only one independent variable and one dependent variable, then it is a simple linear regression. However, if there is more than one independent variable, then it would be called multiple linear regression. Multivariate linear regression is different for it includes multiple correlated dependent variables rather than a single dependent variable.(Freedman, 2009; Rencher & Christensen, 2012)

2.3.3 Definition of machine learning

Machine learning concerns the usage of computer algorithms that continually improve based on data. This differs on what is traditionally done, wherein the model has to be explicitly created.(Friedman, 1998)

2.3.4 Regression and Machine Learning

Linear regression could be used as a predecessor to the current methods used for machine learning. Even though it is less useful than contemporary methods, its simplicity allows us to quickly visualize the rationales for the different techniques that were used to ascend machine learning from a novelty to technique that would revolutionize the future.(Maulud & Abdulazeez, 2020)

2.4 Non-destructive Methods of determining compressive strength

2.4.1 Destructive Methods

Destructive methods are methods of collecting data that destroys the specimen that is used to collect the data (Făcăoaru, 1970). This contrasts with semi-destructive methods wherein the data collection process would cause cosmetic damage (Schabowicz, 2019).

Before there were non-destructive methods, there were destructive methods. The destructive methods are used as a baseline for they are the methods invented earlier (Schabowicz, 2019).

2.4.2 Non-destructive methods

Non-destructive methods of measuring the compressive strength of concrete were made in response to concerns of safety of already built structures. The deterioration of these structures necessitated a way of observing the change between the initial state of the structure with its current state.(Helal et al., 2015)

The two most common methods for non-destructive testing are the rebound hammer test and Ultrasonic Pulse Velocity (UPV) test. (Malek & Kaouther, 2014)

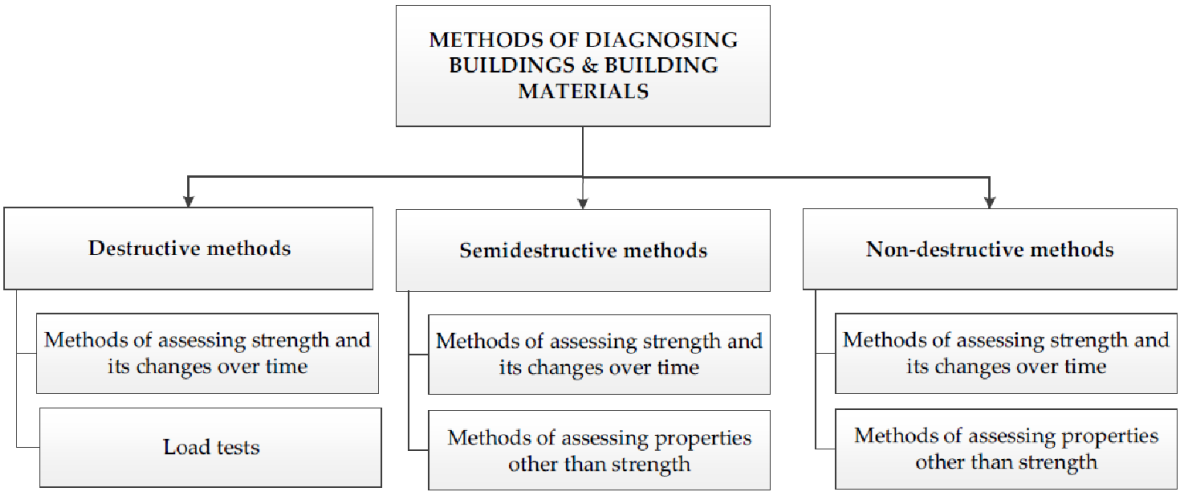


Figure 2.4.1 General classification of non-destructive methods useful for diagnosing buildings and building materials, group into destructive, semi-destructive and non-destructive. (Schabowicz, 2019)

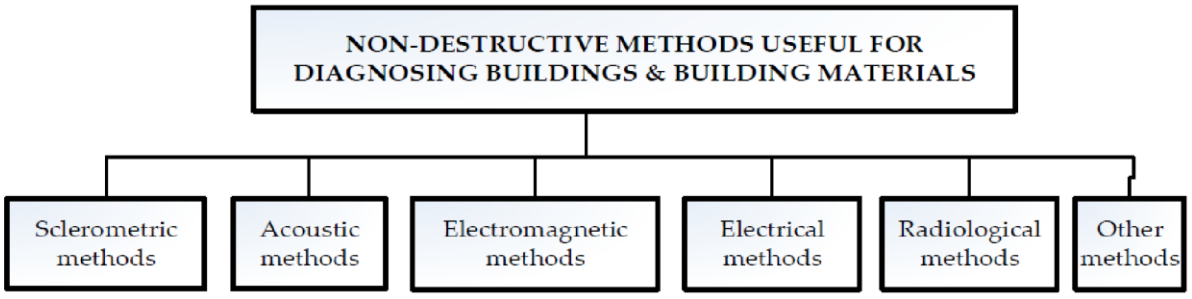


Figure 2.4.2 General classification of non-destructive methods useful for diagnosing buildings and building materials (Schabowicz, 2019)

2.5 MATLAB

2.5.1 Use of MATLAB

MATLAB is a software package that allows us to do mathematics and computing, analyze data, develop algorithms, and do simulation and modeling. The tool uses the MATLAB language.(Knight, 2000)

2.5.2 MATLAB Neural network toolbox

One of the features of MATLAB is its support with regards to the different neural network algorithms. Most notably, its support with regards to the MATLAB neural network toolbox. (Ashour & Alqedra, 2005)

2.6 PCA Analysis

Principal component analysis improves the analysis of neural networks.(Mohamad-Saleh & Hoyle, 2008)

2.7 Similar Previous research

2.7.1 Applications of neural networks

Sergio Lai and Mauro Serra used in 1997 neural networks to predict compressive strength. Destructive tests were used here (Lai & Serra, 1997). Neural networks were also used to predict the slump and compressive strength of high strength concrete (Atici, 2011). Oztas et. al. also predicted the strength of a concrete using neural networks.

(Öztaş et al., 2006)Neural networks have also been used to predict the properties of a dam as it is exposed to the elements for a long amount of time given the local conditions (Mata, 2011). The compressive strength of a no slump concrete was also estimated using neural networks. This paper also introduced adaptive network-based fuzzy inference systems (ANFIS) (Sobhani et al., 2010). Artificial neural networks and fuzzy logic are also used to calculate the properties of a rubberized concrete (Topçu & Sarıdemir, 2008).

Concrete cracks were also predicted using neural networks (Dung, 2019). Asphalt concrete permeability was also calculated using neural networks (Tarefder et al., 2005).

2.7.2 Other methods

Fuzzy logic could also be used in the prediction of compressive strength of concrete.(Özcan et al., 2009)

2.8 Related research on factors considered

2.8.1 Amount of cement in concrete

The amount of cement influences the compressive strength of concrete (Raki et al., 2010). Thomas et. al. saw that the compressive strength would be higher as the amount of cement (kg/m^3) increases.(Thomas et al., 2018)

2.8.2 Amount of aggregate in concrete

Quareshi et. al. used the mix proportion to check the behavior of the concrete. Namely, it is expected that decreasing the proportion of aggregates with respect to cement would increase the compressive strength of the concrete. It has also been found that the quality of the aggregates plays a significant role. (Qureshi et al., 2015)

2.8.3 Amount of recycled concrete aggregate in concrete

It has been found that replacing up to 30% of the coarse aggregates to be used with RCA (Recycled Coarse Aggregate) would provide no significant difference in the compressive strength of concrete. Using above 30% replacement would decrease the compressive strength (Limbachiya et al., 2000). Thomas et. al. however, found that 25% of the coarse aggregates could be replaced with RCA (Thomas et al., 2018).

2.8.4 Amount of water content and water to binder ratio in concrete

Thomas et. al. found that increasing the water to binder ratio would decrease the compressive strength of the concrete (Thomas et al., 2018). The water content could be found by multiplying the water binder ratio with the mass of binder per m^3 of concrete. Binders include materials such as concrete.

2.8.5 Amount of total unit weight in concrete

The total unit weight in concrete has an influence. This is because

the unit weight of concrete is due to the mix design. A lower unit weight is correlated with lower compressive strength and vice versa. Although it would seem beneficial to have a lower unit weight in order to make the structure lighter, the unit weight to be used for design is fixed and thus nonstandard procedures would be needed to exploit the lower weight of the synthesized concrete.(Mohammed et al., 2018; Mohammed & Adamu, 2019)

2.8.6 Amount of granite fines in concrete

It has been found that it is optimal to replace 20% of the river sand with granite fines. However, it is also allowed to replace all the sand with granite fines wherever it would be more economical to us granite fines instead of sand. Sand is also synonymous with fine aggregate. (Joel, 2010)

2.8.7 Amount of fly ash in concrete

Fly ash is able to have pozzolanic properties and thus, it would be of interest to know how it contributes to the concrete. The effect of substituting Portland cement with fly ash has been analyzed. It has been found that using fly ash with fine particle sizes is a sufficient substitute. (Kiattikomol et al., 2001; Tangpagasit et al., 2005)

2.8.8 Amount of ground granulated blast furnace slag and nano silica in concrete

It has been found that replacing 8% of the cement with nano silica would give the most optimal results; increasing the proportion of replacement would reduce the compressive strength of the concrete. The optimal percentage by which the cement would be replaced by slag is 70%. (Toutanji et al., 2004)

2.8.9 Amount of filler in concrete

Fly ash, slag and other cementitious materials could be used as cementitious filler. (Mohammed et al., 2018; Mohammed & Adamu, 2019). Felekoğlu et. al. found that increasing the mineral filler replacing the cement to more than 20% would cause the concrete to be weaker than the concrete without the substitution (Felekoğlu et al., 2006).

2.8.10 Amount of crumb rubber in concrete

There have been investigations as to whether the addition of crumb rubber in concrete would affect its properties. It has been found that increasing the percentage of fine aggregate that would be replaced by crumb rubber would reduce its concrete strength. (Mohammed et al., 2018; Mohammed & Adamu, 2019)

2.8.11 Amount of metakaolin in concrete

It has been seen that the amount of metakaolin has an influence on the compressive strength of concrete. A 10% replacement of cement with metakaolin is the most ideal replacement amount. Metakaolin, just

like silica fumes, are a cementitious material used to replace a small part of cement (Poon et al., 2006). It has also been found that substituting cement with metakaolin is better than substituting a similar percentage of cement with silica fume.(Poon et al., 2006)

2.8.12 Amount of polypropylene fiber in concrete

Ramujee performed research on the appropriate amount of fiver to place in the concrete. It has been found that 1.5% by volume of concrete is the appropriate amount of fiber to use.(Ramujee, 2007)

2.8.13 Dry curing of concrete

Atis et. al. has found that dry curing results in a lower compressive strength than wet curing. They have also found that concrete with silica fumes was more sensitive with regards to whether the concrete has been wet cured or dry cured. (Atiş et al., 2005)

2.8.14 Amount of superplasticizer in concrete

It has been found that the amount of superplasticizer added to the concrete has, by itself, influence on the compressive strength of concrete. It has been found that a 1% ratio of superplasticizer is the most optimal. This proportion corresponds to adding 1000 ml of superplasticizer per 100 kg of cement added. (Alsadey, 2012)

2.8.15 Schmidt Rebound Number

The Schmidt rebound number is a test that could be used to

compare the compressive strength of concrete in the laboratory with the compressive strength of the concrete when deployed on site (Hannachi & Guetteche, 2014). However, even though using the manufacturer provided conversion curve for Schmidt rebound number is not accurate for determining the compressive strength, the conservative nature of the curve should make it still sufficient to determine if the structure is safe. However, using the manufacturer provided curve would not give a reading that is accurate enough to deem the structure unsafe. Other methods would need to be used in order to determine if the structure is unsafe.(Sanchez & Tarranza, 2015)

2.8.16 Ultrasonic Pulse Velocity

Ultrasonic pulse velocity is a reliable way of measuring the difference between the synthesis of the concrete with a given mix design on the lab and on the field. This is highlighted by the fact that a customized calibration curve would need to be created whenever a customized mix design would be used. It had also been found that the UPV is not that much affected by the type of cement or whether the aggregates were initially dry or wet.(Bogas et al., 2013)

2.8.17 Age of concrete

The age of concrete matters since concrete matures and gets stronger in time through curing. This phenomenon could be seen in most of the studies with regards to concrete (J.-I. Kim et al., 2004; J.-K. Kim

et al., 1998). Therefore it is standardized to choose the 28-day strength of concrete. This is the age when concrete is strong enough without the use of accelerators (Nurruddin & Department of Civil Engineering, Universiti Teknologi Petronas, Seri Iskandar, Malaysia, 2018).

Chapter III

Framework

3.1 Conceptual Framework

The data would be filtered out and separated into data that includes the all the non-destructive factors and one that does not. The data without all the non-destructive factors would have the remaining non-destructive test values further removed. To be more specific, the values of the NDT factors would be set to zero. On the figure, the data with NDT is the data with ultrasonic pulse velocity (UPV) and rebound number (RN). The data without NDT would be data without UPV and RN.

The data with NDTs would be used to create the primary component analysis (PCA), linear regression analysis, analysis using other models, and analysis using tweaked neural networks. The analysis using other models and linear regression analysis is useful for setting a baseline in terms of the mean squared error (MSE) of the model. This would make it much more likely to create a model that is better than the unoptimized versions of the other models, justifying the use of neural networks.

The primary component analysis and the linear regression analysis would be used to find the best NDT data. In this case, it would

find the factors that would contribute the most to the compressive strength of concrete. The original data would then be again run into the analysis but this time, only the important factors would have values. The rest would be zeroed out. The analysis would produce NN, linear regression and other models. The other models would be to ensure that the MSE of the model would be low.

The data without NDT factors would be used to create the primary component analysis (PCA), linear regression analysis, analysis using other models, and analysis using tweaked neural networks. The analysis using other models and linear regression analysis is useful for setting a baseline in terms of the mean squared error (MSE) of the model. This would make it much more likely to create a model that is better than the unoptimized versions of the other models, justifying the use of neural networks.

The primary component analysis and the linear regression analysis would be used to find the best data without NDT. In this case, it would find the factors that would contribute the most to the compressive strength of concrete. The original data would then be again run into the analysis but this time, only the important factors would have values. The rest would be zeroed out. The analysis would produce NN, linear regression and other models. The other models would be to ensure that the MSE of the model would be low.

The primary component analysis and the linear regressions would be used to narrow down to factors that significantly contribute to the compressive strength of concrete. The linear regressions are added in conjunction with the primary component analysis for the primary component analysis did not consider the non-destructive factors nor the age of concrete to contribute significantly to the compressive strength. The MATLAB has been used to create a model using the factors to be considered. The regression learner is used to test with regards to multiple models while the neural network fitting tool is used to tweak the neural network. The results of the models using non-destructive testing would be differentiated to those that did not using criteria such as MSE and r squared to compare results from destructive methods with non-destructive methods. These would determine if adding non-destructive test factors would improve accuracy. The three objectives are the requisite for modeling the compressive strength of concrete from non-destructive tests using machine learning to be done. This is since the said objectives would be a guide to find the correct information about the matter and to explain the model derived.

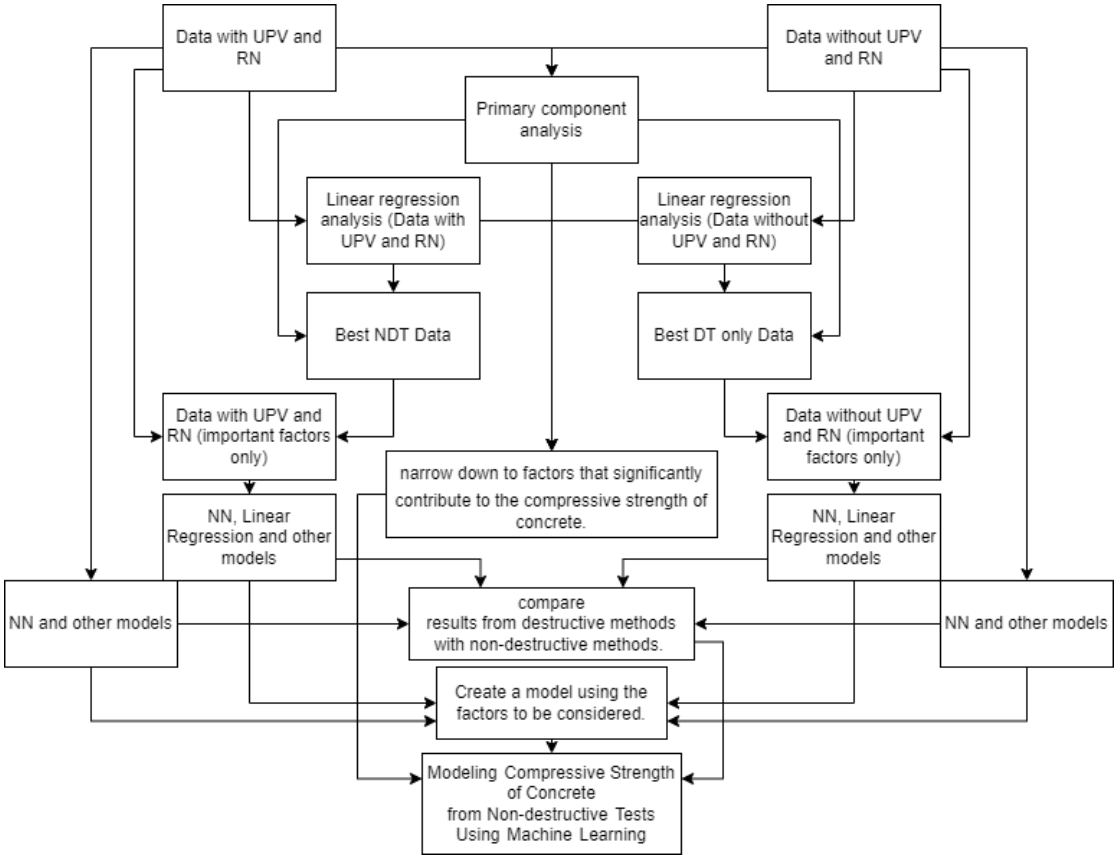


Figure 3.1.1 Conceptual Framework

3.2 Theoretical Framework

3.1.1 Ultrasonic Pulse Velocity Test

An ultrasonic pulse velocity (UPV) test is an in-situ, nondestructive test to check the quality of concrete. In this test, the strength and quality of concrete is assessed by measuring the velocity of an ultrasonic pulse passing through a concrete structure.

This test is conducted by passing a pulse of ultrasonic through concrete to be tested and measuring the time taken by pulse to get through the structure. Higher velocities indicate good quality and continuity of the material, while slower velocities may indicate concrete with many cracks or voids.

Ultrasonic testing equipment includes a pulse generation circuit, consisting of electronic circuit for generating pulses and a transducer for transforming electronic pulse into mechanical pulse having an oscillation frequency in range of 40 kHz to 50 kHz, and a pulse reception circuit that receives the signal.(Amini et al., 2016)

3.1.2 Rebound Number

Rebound Hammer test is a Non-destructive testing method of concrete which provide a convenient and rapid indication of the compressive strength of the concrete. The rebound hammer is also called as Schmidt hammer that consist of a spring-controlled mass that

slides on a plunger within a tubular housing. When the plunger of rebound hammer is pressed against the surface of concrete, a spring-controlled mass with a constant energy is made to hit concrete surface to rebound back. The extent of rebound, which is a measure of surface hardness, is measured on a graduated scale. This measured value is designated as Rebound Number (rebound index). Concrete with low strength and low stiffness will absorb more energy to yield in a lower rebound value. (Szilagyi & Borosnyoi, 2009)

3.1.3 Artificial neural network

The study will use an Artificial Neural Network (ANN) to model the compressive strength. The idea would be to leverage the currently existing literature on the internet to perform the technique. Data could be found by asking or by leveraging graphs provided in the journals.

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called *edges*. Neurons and edges typically have a *weight* that adjusts as learning proceeds. The weight increases or

decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times. (Schmidhuber, 2015)

Chapter IV

Research Methodology

4.1 Research Method

The research was done by using MATLAB to process the data. Web Plot Digitizer was used to help convert the points in the charts into tabular data. The data came from journals and other reliable sources.

4.1.1 Input and tool and techniques (ITTO) and further explanation for each of the objectives

Create a model using the factors to be considered. The inputs are going to be the factors to be considered. The tools and techniques are the methods that are going to be used for gathering the factors and the machine learning algorithm itself. The output would be a model, a description of how the concrete strength using the factors.

To narrow down the search to factors that significantly contribute to the compressive strength of concrete. This is useful to see which parameters create a significant difference to the compressive strength of concrete. The inputs are going to be the factors to be considered. The tools and techniques are principal component analysis and feature

elimination. The objective would be a smaller set of features.

To compare results from destructive methods with non-destructive methods. The input would be the results from destructive methods with non-destructive methods, more specifically the same inputs as used for the non-destructive tests. This would be used to gauge the extent by which the results are different using non-destructive testing than destructive testing. The tools and techniques are the methods that are going to be used for gathering the factors and the machine learning algorithm itself. This is like the case with non-destructive concrete since it would both need a similar approach. The output would be a separate model considering only destructive concrete measurements. This would be used to compare one against the other. Note that a separate model needs to be created for non-destructive testing simply to compare itself against destructive tests due to the difference in factors.

4.2 Research Design

The data would be the previous research in the field of non-destructive testing that tries to find out the compressive strength of a concrete using non-destructive methods.

4.3 Data Cleansing

The graph that would be placed on Web Plot Digitizer would be cleaned by removing formulas in the pictures of charts. Outrageous values from the same program would also be removed. Visual inspection will be used to filter out discrepant points.

4.4 Collection of data

The first step was to collect data from various journals. The journals considered included the following:

Table 4.4-1 Table of journals considered for addition

Author	Title	Publication Title	Vol.	Issue	Publication Year
Noori, Ali S.; Oweed, Khalid M.; Raouf, Raouf M.; Abdulrehman, Mohammed A.	The relation between destructive and non-destructive tests of geopolymer concrete	Materials Today: Proceedings	42	0	2021

Author	Title	Publication Title	Vol.	Issue	Publication Year
Latif Al-Mufti, R.; Fried, A.N.	The early age non-destructive testing of concrete made with recycled concrete aggregate	Construction and Building Materials	37	0	2012
Alwash, Maitham; Sbartaï, Zoubir Mehdi; Breysse, Denys	Non-destructive assessment of both mean strength and variability of concrete: A new bi-objective approach	Construction and Building Materials	113	0	2016

Author	Title	Publication Title	Vol.	Issue	Publication Year
Ivanchev, Ivan	Experimental Determination of Modulus of Elasticity of Concrete by Non-Destructive Ultrasonic Pulse Velocity Method	Int. J. Res. Appl. Sci. Eng. Technol	6	0	2018
Malek, Jedidi; Kaouther, Machta	Destructive and Non-destructive Testing of Concrete Structures	Jordan Journal of Civil Engineering	8	4	2014
Poorarbabi, Ali; Ghasemi, Mohammadreza; Azhdary Moghaddam, Mehdi	Concrete compressive strength prediction using non-destructive tests through response surface methodology	Ain Shams Engineering Journal	11	4	2020

Author	Title	Publication Title	Vol.	Issue	Publication Year
Amini, Kamran; Jalalpour, Mehdi; Delatte, Norbert	Advancing concrete strength prediction using non-destructive testing: Development and verification of a generalizable model	Construction and Building Materials	102	0	2016
Singh, Navdeep; Singh, S. P.	Evaluating the performance of self-compacting concretes made with recycled coarse and fine aggregates using non-destructive testing techniques	Construction and Building Materials	181	0	2018

Author	Title	Publication Title	Vol.	Issue	Publication Year
Velay-Lizancos, Mirian; Martinez-Lage, Isabel; Azenha, Miguel; Granja, Jose; Vazquez-Burgo, Pablo	Concrete with fine and coarse recycled aggregates: E-modulus evolution, compressive strength, and non-destructive testing at early ages	Construction and Building Materials	193	0	2018
Aseem, Ahmed; Baloch, Waqas Latif; Khushnood, Rao Arsalan; Mushtaq, Arslan	Structural health assessment of fire damaged building using non-destructive testing and micro-graphical forensic analysis: a case study	Case Studies in Construction Materials	11	0	2019
Asteris, Panagiotis G.; Mokos, Vaseilios G.	Concrete compressive strength using artificial neural networks	Neural Computing and Applications	32	15	2020

Author	Title	Publication Title	Vol.	Issue	Publication Year
Jasiński, Rados\law; Drobiec, \Lukasz; Mazur, Wojciech	Validation of selected non-destructive methods for determining the compressive strength of masonry units made of autoclaved aerated concrete	Materials	12	3	2019
Rahim, Mustaqqim Abdul; Shahidan, Shahiron; Lee, Choon Onn; Bahari, Nur Amira Afiza Saiful; Abd Rahman, Norashidah; Ayob, Afizah	The behavior of non-destructive test for different grade of concrete	International Journal of Integrated Engineering	12	9	2020

Author	Title	Publication Title	Vol.	Issue	Publication Year
Wolfs, R. J. M.; Bos, F. P.; Salet, T. A. M.	Correlation between destructive compression tests and non-destructive ultrasonic measurements on early age 3D printed concrete	Construction and Building Materials	181	0	2018
Kovler, Konstantin; Wang, Fengzhe; Muravin, Boris	Testing of concrete by rebound method: Leeb versus Schmidt hammers	Materials and Structures	51	5	2018

Author	Title	Publication Title	Vol.	Issue	Publication Year
Mohammed, Bashar S.; Adamu, Musa; Liew, Mohd Shahir	Evaluating the effect of crumb rubber and nano silica on the properties of high-volume fly ash roller compacted concrete pavement using non-destructive techniques	Case studies in construction materials	8	0	2018
Tan, Yongshan; Yu, Hongfa; Mi, Renjie; Zhang, Yan	Compressive strength evaluation of coral aggregate seawater concrete (CAC) by non-destructive techniques	Engineering Structures	176	0	2018

Author	Title	Publication Title	Vol.	Issue	Publication Year
Tchamdjou, Willy H. Juimo; Cherradi, Toufik; Abidi, Moulay Larbi; Pereira-de-Oliveira, Luiz A.	Mechanical properties of lightweight aggregates concrete made with cameroonian volcanic scoria: Destructive and non-destructive characterization	Journal of Building Engineering	16	0	2018
Mohammed, Bashar S.; Adamu, Musa	Non-destructive evaluation of nano silica-modified roller-compacted rubbercrete using combined SonReb and response surface methodology	Road Materials and Pavement Design	20	4	2019

Author	Title	Publication Title	Vol.	Issue	Publication Year
Kazemi, Mostafa; Madandoust, Rahmat; de Brito, Jorge	Compressive strength assessment of recycled aggregate concrete using Schmidt rebound hammer and core testing	Construction and Building Materials	224	0	2019
Sreenivasulu, C.; Guru Jawahar, J.; Sashidhar, C.	Predicting compressive strength of geopolymer concrete using NDT techniques	Asian Journal of Civil Engineering	19	4	2018

From the following table, here are the journals that were included in the dataset:

Table 4.4-2 Table of journals added in the dataset

Author	Title	Publication Title	Publication Year
Noori, Ali S.; Oweed, Khalid M.; Raouf, Raouf M.; Abdulrehman, Mohammed A.	The relation between destructive and non-destructive tests of geopolymer concrete	Materials Today: Proceedings	2021
Poorarbabi, Ali; Ghasemi, Mohammadreza; Azhdary Moghaddam, Mehdi	Concrete compressive strength prediction using non-destructive tests through response surface methodology	Ain Shams Engineering Journal	2020

Author	Title	Publication Title	Publication Year
Singh, Navdeep; Singh, S. P.	Evaluating the performance of self-compacting concretes made with recycled coarse and fine aggregates using non-destructive testing techniques	Construction and Building Materials	2018
Rahim, Mustaqqim Abdul; Shahidan, Shahiron; Lee, Choon Onn; Bahari, Nur Amira Afiza Saiful; Abd Rahman, Norashidah; Ayob, Afizah	The behavior of non-destructive test for different grade of concrete	International Journal of Integrated Engineering	2020
Kovler, Konstantin; Wang, Fengzhe; Muravin, Boris	Testing of concrete by rebound method: Leeb versus Schmidt hammers	Materials and Structures	2018

Author	Title	Publication Title	Publication Year
Mohammed, Bashar S.; Adamu, Musa; Liew, Mohd Shahir	Evaluating the effect of crumb rubber and nano silica on the properties of high-volume fly ash roller compacted concrete pavement using non-destructive techniques	Case studies in construction materials	2018

Author	Title	Publication Title	Publication Year
Mohammed, Bashar S.; Adamu, Musa	Non-destructive evaluation of nano silica-modified roller-compacted rubbercrete using combined SonReb and response surface methodology	Road Materials and Pavement Design	2019
Kazemi, Mostafa; Madandoust, Rahmat; de Brito, Jorge	Compressive strength assessment of recycled aggregate concrete using Schmidt rebound hammer and core testing	Construction and Building Materials	2019

Author	Title	Publication Title	Publication Year
Sreenivasulu, C.; Guru Jawahar, J.; Sashidhar, C.	Predicting compressive strength of geopolymer concrete using NDT techniques	Asian Journal of Civil Engineering	2018

There were also journals that showed promise, but the data has not been planned to be included since the mix design used to create the data was not found:

Table 4.4-3 Table of journals not included and their reasons for non-inclusion

Author	Title	Publication Title	Reason for non-inclusion
Latif Al-Mufti, R.; Fried, A.N.	The early age non-destructive testing of concrete made with recycled concrete aggregate	Construction and Building Materials	weight of cement etc. could not be found in text

Author	Title	Publication Title	Reason for non-inclusion
Alwash, Maitham; Sbartaï, Zoubir Mehdi; Breysse, Denys	Non-destructive assessment of both mean strength and variability of concrete: A new bi-objective approach	Construction and Building Materials	no mix design
Ivanchev, Ivan	Experimental Determination of Modulus of Elasticity of Concrete by Non-Destructive Ultrasonic Pulse Velocity Method	Int. J. Res. Appl. Sci. Eng. Technol	EN 12390-2:2009 Acessible; I. Dobreva inaccessable
Amini, Kamran; Jalalpour, Mehdi; Delatte, Norbert	Advancing concrete strength prediction using non-destructive testing: Development and verification of a generalizable model	Construction and Building Materials	no mix data
Asteris, Panagiotis G.; Mokos, Vaseilios G.	Concrete compressive strength using artificial neural networks	Neural Computing and Applications	meta-source paper (Logothetis LA (1978)) not found

Author	Title	Publication Title	Reason for non-inclusion
Wolfs, R. J. M.; Bos, F. P.; Salet, T. A. M.	Correlation between destructive compression tests and non-destructive ultrasonic measurements on early age 3D printed concrete	Construction and Building Materials	proprietary materials
Tan, Yongshan; Yu, Hongfa; Mi, Renjie; Zhang, Yan	Compressive strength evaluation of coral aggregate seawater concrete (CAC) by non-destructive techniques	Engineering Structures	mix proportion abstracted from results

From there, the data that have been found from the selected sources has been combined into a table. The table contains the following variables:

- Cement (kg/m^3)
- Coarse aggregates (kg/m^3)
- Fine aggregates (kg/m^3)
- Coarse RCA (kg/m^3)

- Fine RCA (kg/m^3)
- Water content (kg/m^3)
- Water to binder ratio
- Total Unit Weight (kg/m^3)
- Granite Fines (kg/m^3)
- Fly ash content (kg/m^3)
- Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)
- Nano Silica (kg/m^3)
- Filler (kg/m^3)
- Crumb Rubber (kg/m^3)
- Metakaolinite Content (kg/m^3)
- polypropylene fibre (% by volume)
- dry curing
- Superplasticizer (%)
- Age of concrete (days)
- Compressive strength (MPa)

The missing data would be filled whenever it is reasonable to have it filled. For instance, the studies that do not use granite fines would have 0 kg/m^3 of granite fines in their concrete. Missing data by which there is no suitable value to add to the missing data would be left as blank.

The data (which would be placed in a table) would then be filtered out. The columns in the table would have the relevant filters added then moved to another set of cells. This is done to remove entries with missing data (that has not been filled up) with regards to the columns (factors) that would be used.

The data would then be exported into MATLAB. The way to do it is to access the workbook with the relevant data using MATLAB. This would give a wizard by which data could be imported as a MATLAB table.

To create the numerical arrays needed for Neural Net Fitting tool under the Deep Learning Toolbox, two numerical arrays are created, one which has the inputs, which are the factors that are theorized to influence the compressive strength and the other is the output, which is the compressive strength itself.

The MATLAB table would then be inputted to the Regression Learner tool to use all the available models in Regression Learner tool

at default settings to test the data. A model that would be sent for further analysis would be the model with the lowest root mean squared error (RMSE) using the validation dataset. The other model that would be sent for further analysis would be the linear regression and the neural network which has the lowest RMSE. The linear regression is sent for further analysis since it would be easy to interpret; the value predicted by the regression could be found by summing the product of the regression coefficients with the input variable and adding to it the regression intercept. The neural network would be used for the sake of comparison. The neural network by which the size of the hidden layers has been optimized to bring a better result is expected to be better than an unoptimized neural network.

The Regression Learner tool could also be used to find the primary components, the set of components that would be able to explain 95% of the variance of the model. In other words, the factors could be summed up into a smaller set of primary components that could explain 95% of the changes with regards to the data.

The primary components could then be used to find out the factors that influence the compressive strength of concrete the most. The idea with the analysis is that if the factor has a greater than 5% contribution to the principal components on average, then the factor is construed to be important since they have a considerable contribution

to the principal components, which would imply that the factor contributes appreciably to the variation of data, in that the compressive strength is changed remarkably by the influence of the factor shortlisted.

The numerical arrays would then be used as the inputs and the outputs of the artificial neural network. The hidden layer of the neural network would be modified until the model is able to reach close to an equilibrium with regards to train mean squared error (MSE) prevailing or the validation MSE is prevailing. The ideal hidden neural network is one where the train, test, and validation MSE is as similar as they could be while the MSE is smaller than the other techniques analyzed. Once the ideal neural network has been found, the results of the neural network are analyzed further. Further analysis includes extracting relevant tables and graphs from the model and extraction of the created model itself, such that it could be used to predict future data.

The different methods are going to be tabulated with regards to their R-Squared and MSE. This is to ensure that model found fits the criteria that would be needed to say that the model found is optimal.

4.5 Summary of Procedures

The flow of the study begins by looking at the different journal articles. The data from the articles could be sourced using tables of the

data, if available, or by using web plot digitizer. The web plot digitizer would make the extraction of the data easier by making it less error prone. It would allow less error by having the software pick out the data and put it in a spreadsheet. There would also need to be some fiddling so that the figures would be seen correctly and some manual inclusion of points in some circumstances.

This all would allow me to have the data from journal articles. After all this, I would compile the data based on all the factors considered. I would also fill the missing data afterwards, taking note to fill data only when reasonable and to leave unfilled data blank.

After this, the data would be filtered out and separated into data that includes the all the non-destructive factors and one that does not. The data without all the non-destructive factors would have the remaining non-destructive test values further removed. To be more specific, the values of the NDT factors would be set to zero. On the figure, the data with NDT is the data with ultrasonic pulse velocity (UPV) and rebound number (RN). The data without NDT would be data without UPV and RN.

The data with NDTs would be used to create the primary component analysis (PCA), linear regression analysis, analysis using other models, and analysis using tweaked neural networks. The analysis using other models and linear regression analysis is useful for setting a

baseline in terms of the mean squared error (MSE) of the model. This would make it much more likely to create a model that is better than the unoptimized versions of the other models, justifying the use of neural networks.

The primary component analysis and the linear regression analysis would be used to find the best NDT data. In this case, it would find the factors that would contribute the most to the compressive strength of concrete. The original data would then be again run into the analysis but this time, only the important factors would have values. The rest would be zeroed out. The analysis would produce NN, linear regression and other models. The other models would be to ensure that the MSE of the model would be low.

The data without NDT factors would be used to create the primary component analysis (PCA), linear regression analysis, analysis using other models, and analysis using tweaked neural networks. The analysis using other models and linear regression analysis is useful for setting a baseline in terms of the mean squared error (MSE) of the model. This would make it much more likely to create a model that is better than the unoptimized versions of the other models, justifying the use of neural networks.

The primary component analysis and the linear regression analysis would be used to find the best data without NDT. In this case,

it would find the factors that would contribute the most to the compressive strength of concrete. The original data would then be again run into the analysis but this time, only the important factors would have values. The rest would be zeroed out. The analysis would produce NN, linear regression and other models. The other models would be to ensure that the MSE of the model would be low.

The best model would be decided based on the MSE of the NNs that have factors removed. This is because the reduced models are sufficiently good when compared to the unreduced versions. Comparing the models with NDT factors to those without NDT factors is also to see how NDT factors would influence the model.

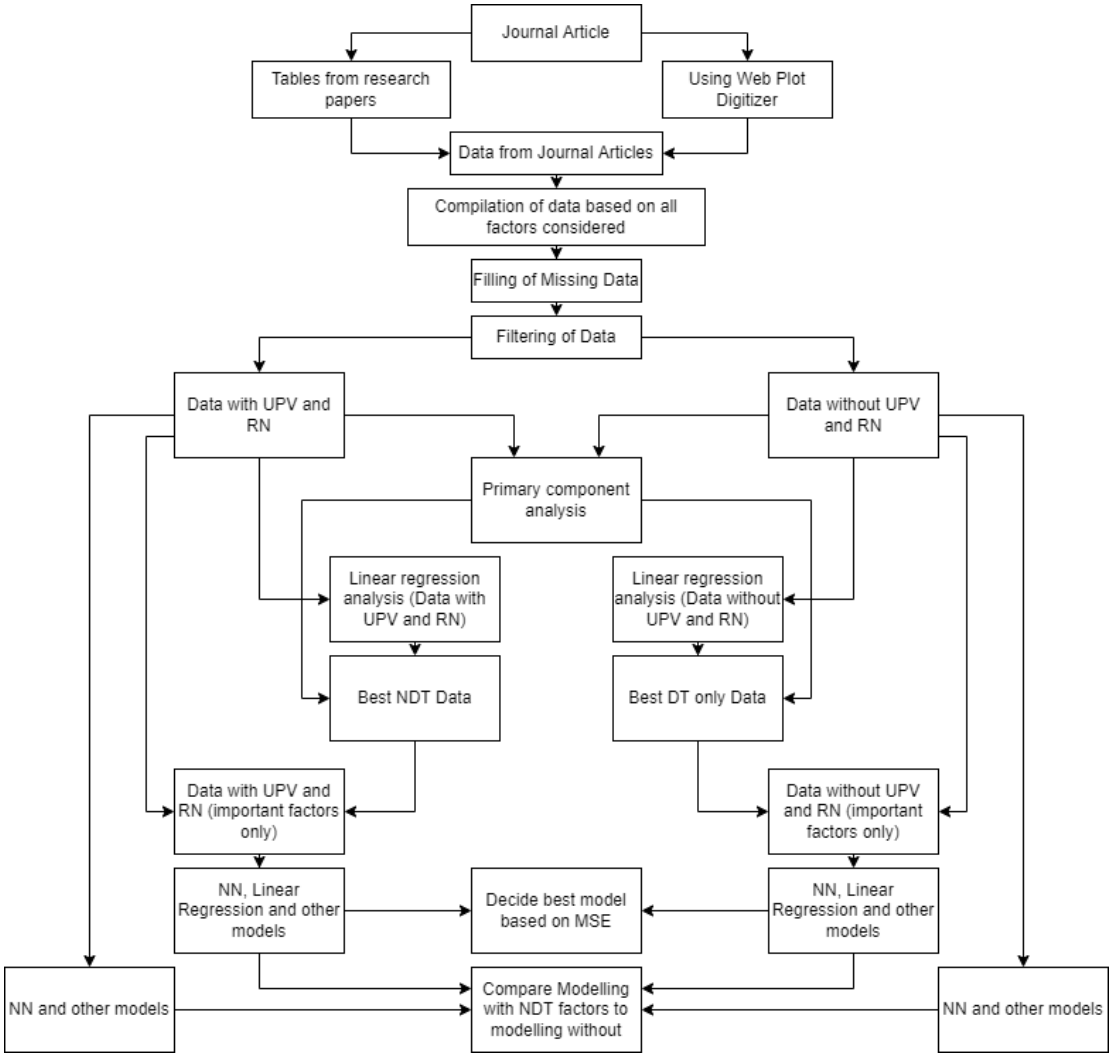


Figure 4.5.1 Summary of research

Chapter V

Results and Discussion

5.1 Primary Component Analysis

The primary component analysis was performed to find out which of the variables were most impactful for the analysis. Primary component analysis would be useful since it would be able to see which of the factors contribute the most to the models.

Table 5.1-1 Breakdown using primary component analysis.

Labels	PC1	PC2	PC3	PC4	PC5
Cement (kg/m^3)	-0.1997	0.0066	0.0345	-0.5607	0.4879
Coarse aggregates (kg/m^3)	0.7429	-0.2102	-0.4345	-0.113	0.0785
Fine aggregates (kg/m^3)	-0.0683	0.8883	-0.1492	0.0648	-0.0588
Coarse RCA (kg/m^3)	-0.0341	-0.1721	0.4477	0.5786	0.4066
Fine RCA (kg/m^3)	0.0176	-0.1089	0.5371	-0.4535	-0.4396
Water content (kg/m^3)	-0.0991	-0.0697	0.0783	-0.0853	-0.0256
Water to binder ratio	-0.0003	-0.0002	0.0001	0	-0.0002
Total Unit Weight (kg/m^3)	0.6113	0.3357	0.5385	-0.0698	0.1157
Granite Fines (kg/m^3)	0.0301	-0.0193	-0.0029	0.0559	-0.0924
Fly ash content (kg/m^3)	0.102	-0.0161	0.0373	0.3166	-0.3234
Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)	0.0371	-0.0169	-0.0064	0.0701	-0.1108
Nano Silica (kg/m^3)	0.0011	0.0018	0.0006	-0.0007	0.0075
Filler (kg/m^3)	0.0298	0.0507	0.016	-0.0181	0.2051
Crumb Rubber (kg/m^3)	0.0463	0.0622	0.0194	-0.0381	0.4534
Metakaolinite Content (kg/m^3)	0.0516	0.0085	-0.0179	0.0778	-0.0788
polypropylene fibre (% by volume)	0	0	0	0	0
dry curing	0	0	0	0	0
Superplasticizer (%)	0.0013	-0.0001	-0.0003	0.0029	-0.0039

(Schmidt) Rebound number	0.0073	-0.0004	0.009	-0.0023	0.0117
UPV (km/s)	-0.0002	0.0001	0.0002	-0.0013	0.0017
Age of concrete (days)	-0.008	-0.016	0.0137	-0.0023	-0.0141
Compressive strength (MPa)					

The primary components were chosen by creating as many principal components as needed to explain 95% of the variance in the data. The analysis was able to see that 5 principal components are only needed.

Table 5.1-2 The values showing the sum of the multiplier applied to the principal components. The values in green are those whose sum is greater than 0.25

Absolute value of Primary Components	PC1	PC2	PC3	PC4	PC5	Sum	Rank of sums
Cement (kg/m^3)	0.1997	0.0066	0.0345	0.5607	0.4879	1.2894	5
Coarse aggregates (kg/m^3)	0.7429	0.2102	0.4345	0.113	0.0785	1.5791	3
Fine aggregates (kg/m^3)	0.0683	0.8883	0.1492	0.0648	0.0588	1.2294	6
Coarse RCA (kg/m^3)	0.0341	0.1721	0.4477	0.5786	0.4066	1.6391	2
Fine RCA (kg/m^3)	0.0176	0.1089	0.5371	0.4535	0.4396	1.5567	4
Water content (kg/m^3)	0.0991	0.0697	0.0783	0.0853	0.0256	0.358	9
Water to binder ratio	0.0003	0.0002	0.0001	0	0.0002	0.0008	19
Total Unit Weight (kg/m^3)	0.6113	0.3357	0.5385	0.0698	0.1157	1.671	1

Granite Fines (kg/m^3)	0.0301	0.0193	0.0029	0.0559	0.0924	0.2006	13
Fly ash content (kg/m^3)	0.102	0.0161	0.0373	0.3166	0.3234	0.7954	7
Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)	0.0371	0.0169	0.0064	0.0701	0.1108	0.2413	11
Nano Silica (kg/m^3)	0.0011	0.0018	0.0006	0.0007	0.0075	0.0117	16
Filler (kg/m^3)	0.0298	0.0507	0.016	0.0181	0.2051	0.3197	10
Crumb Rubber (kg/m^3)	0.0463	0.0622	0.0194	0.0381	0.4534	0.6194	8
Metakaolinite Content (kg/m^3)	0.0516	0.0085	0.0179	0.0778	0.0788	0.2346	12
polypropylene fibre (% by volume)	0	0	0	0	0	0	21
dry curing	0	0	0	0	0	0	21
Superplasticizer (%)	0.0013	0.0001	0.0003	0.0029	0.0039	0.0085	17
(Schmidt) Rebound number	0.0073	0.0004	0.009	0.0023	0.0117	0.0307	15
UPV (km/s)	0.0002	0.0001	0.0002	0.0013	0.0017	0.0035	18
Age of concrete (days)	0.008	0.016	0.0137	0.0023	0.0141	0.0541	14
Compressive strength (MPa)	0	0	0	0	0	0	21

The table shows the influence of a factor in the composition of the primary component. The sum of 0.25 is chosen as the breakoff point since $0.05 \times 5 = 0.25$. The factor of 0.25 was chosen through a reasoning like the Bonferroni correction, in that the sum is used to ensure that a false positive would not be chosen.

It could be seen that using the said analysis, the most significant factors are cement, coarse and fine natural aggregates, coarse and fine recycled aggregates, water content, total unit weight, fly ash content, filler and crumb rubber.

The reason for the almost zero water to binder ratio is that the water to binder ratio is the ratio between the water over the binders that exist. The value of adding the water to binder ratio could be supplanted by adding the water content and content of the binders into the model.

It should be considered however, that the variance of the other factors may not be considered significant under PCA since they are rightfully declared to be zero for most of the samples used. This shows why PCA would not be used.

Table 5.1-3 Breakdown using primary component analysis for DT only.

Labels	PC1	PC2	PC3
Cement (kg/m^3)	0.1109	0.0203	0.5531
Coarse aggregates (kg/m^3)	-0.6238	0.1808	0.3061
Fine aggregates (kg/m^3)	0.0013	0.5792	-0.4791
Coarse RCA (kg/m^3)	0.7332	-0.0878	0.0142
Fine RCA (kg/m^3)	0	0	0
Water content (kg/m^3)	0.0551	-0.0015	0.2681
Water to binder ratio	0	-0.0001	0.0002
Total Unit Weight (kg/m^3)	0.2325	0.7807	0.3372
Granite Fines (kg/m^3)	0	0	0
Fly ash content (kg/m^3)	-0.0103	0.0238	-0.0906

Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)	0	0	0
Nano Silica (kg/m^3)	-0.0011	0.0028	-0.0077
Filler (kg/m^3)	-0.0304	0.0774	-0.2135
Crumb Rubber (kg/m^3)	-0.0525	0.0879	-0.3605
Metakaolinite Content (kg/m^3)	0	0	0
polypropylene fibre (% by volume)	0.0001	0	0.0001
dry curing	0.0003	0.0001	0.001
Superplasticizer (%)	0.0002	0.0001	0.0009
(Schmidt) Rebound number	0	0	0
UPV (km/s)	0	0	0
Age of concrete (days)	0.0077	-0.0077	0.0356
Compressive strength (MPa)			

Table 5.1-4 The values showing the sum of the multiplier applied to the principal components. The values in green are those whose sum is greater than 0.25

Absolute value of Primary Components	PC1	PC2	PC3	Sum	Rank of sums
Cement (kg/m^3)	0.1109	0.0203	0.5531	0.6843	5
Coarse aggregates (kg/m^3)	0.6238	0.1808	0.3061	1.1107	2
Fine aggregates (kg/m^3)	0.0013	0.5792	0.4791	1.0596	3
Coarse RCA (kg/m^3)	0.7332	0.0878	0.0142	0.8352	4
Fine RCA (kg/m^3)	0	0	0	0	19
Water content (kg/m^3)	0.0551	0.0015	0.2681	0.3247	7
Water to binder ratio	0	0.0001	0.0002	0.0003	14
Total Unit Weight (kg/m^3)	0.2325	0.7807	0.3372	1.3504	1

Granite Fines (kg/m^3)	0	0	0	0	19
Fly ash content (kg/m^3)	0.0103	0.0238	0.0906	0.1247	9
Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)	0	0	0	0	19
Nano Silica (kg/m^3)	0.0011	0.0028	0.0077	0.0116	11
Filler (kg/m^3)	0.0304	0.0774	0.2135	0.3213	8
Crumb Rubber (kg/m^3)	0.0525	0.0879	0.3605	0.5009	6
Metakaolinite Content (kg/m^3)	0	0	0	0	19
polypropylene fibre (% by volume)	0.0001	0	0.0001	0.0002	15
dry curing	0.0003	0.0001	0.001	0.0014	12
Superplasticizer (%)	0.0002	0.0001	0.0009	0.0012	13
(Schmidt) Rebound number	0	0	0	0	19
UPV (km/s)	0	0	0	0	19
Age of concrete (days)	0.0077	0.0077	0.0356	0.051	10
Compressive strength (MPa)	0	0	0	0	19

It could be seen that using the said analysis, the most significant factors are cement, coarse and fine natural aggregates, coarse recycled aggregates, water content, total unit weight, fly ash content, filler and crumb rubber. The only difference could be attributed to the fact that the DT dataset does not have fine aggregates.

5.2 Analysis of Non-destructive Factors

5.2.1 Linear Regression

Linear regression is used here since it is the most intuitive method by which a data analysis could be understood. Linear regression is of form $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$, which makes it very intuitive to understand and use.

Table 5.2-1 Result using linear regression

	Estimate	SE	tStat	pValue
(Intercept)	-60.221	8.0389	-7.4912	1.20E-12
Cementkgm3	-0.1468	0.0292	-5.0212	9.82E-07
CoarseAggregateskgm3	-0.1855	0.0286	-6.476	5.02E-10
FineAggregateskgm3	-0.1895	0.0287	-6.6062	2.39E-10
CoarseRCAkgm3	-0.1859	0.0287	-6.4848	4.77E-10
FineRCAkgm3	-0.1874	0.0287	-6.5302	3.69E-10
WaterContentkgm3	-0.1374	0.0354	-3.8827	0.00013
WaterToBinderRatio	12.98	6.4561	2.0106	0.04545
TotalUnitWeightkgm3	0.1899	0.0287	6.6251	2.14E-10
GraniteFineskgm3	-0.1958	0.0294	-6.6597	1.76E-10
FlyAshContentkgm3	-0.1731	0.0301	-5.7493	2.62E-08
GroundGranulatedBlastFurnaceSlag GGBSkgm3	-0.2173	0.0322	-6.7448	1.07E-10
NanoSilicakgm3	0.1069	0.1511	0.7072	0.4801
Fillerkgm3	0.1614	0.0288	5.6106	5.37E-08
CrumbRubberkgm3	-0.0704	0.014	-5.0427	8.87E-07
MetakaoliniteContentkgm3	-0.2202	0.0312	-7.0588	1.68E-11
polypropyleneFibreByVolume	0	0	NaN	NaN
dryCuring	0	0	NaN	NaN
Superplasticizer	13.063	1.6571	7.8828	1.01E-13
SchmidtReboundNumber	0.8024	0.055	14.58	3.41E-35
UPVkms	7.1543	1.07	6.686	1.51E-10
AgeOfConcretedays	-0.0087	0.0074	-1.1639	0.24558

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed. The result from the linear regression shows the importance of each of the variables and coefficient that they would add to the model.

Most notably, it could be seen that water to binder ratio, nano silica weight per volume of concrete, and the age of concrete is not significant.

It could also be seen that polypropylene Fiber by Volume, whether the concrete is dry cured or not are not factors in the dataset. This is because these factors would have been included in the other split of the data. The other split of the data would not contain any non-destructive testing methods.

We know however through various studies that the age of concrete matters. This paradox could be explained by other factors such the Schmidt rebound number and ultrasonic pulse velocity as being able

to relay the same information with regards to the state of the concrete, on the matter of its compressive strength.

Table 5.2-2 Model training results

RMSE (Validation)	2.7205
R-Squared (Validation)	0.95
MSE (Validation)	7.4013
MAE (Validation)	2.0017
Prediction speed	~8600 obs/sec
Training time	11.203 sec

Table 5.2-3 Model parameters

Model Type	
Preset	Linear
Terms	Linear
Robust option	Off

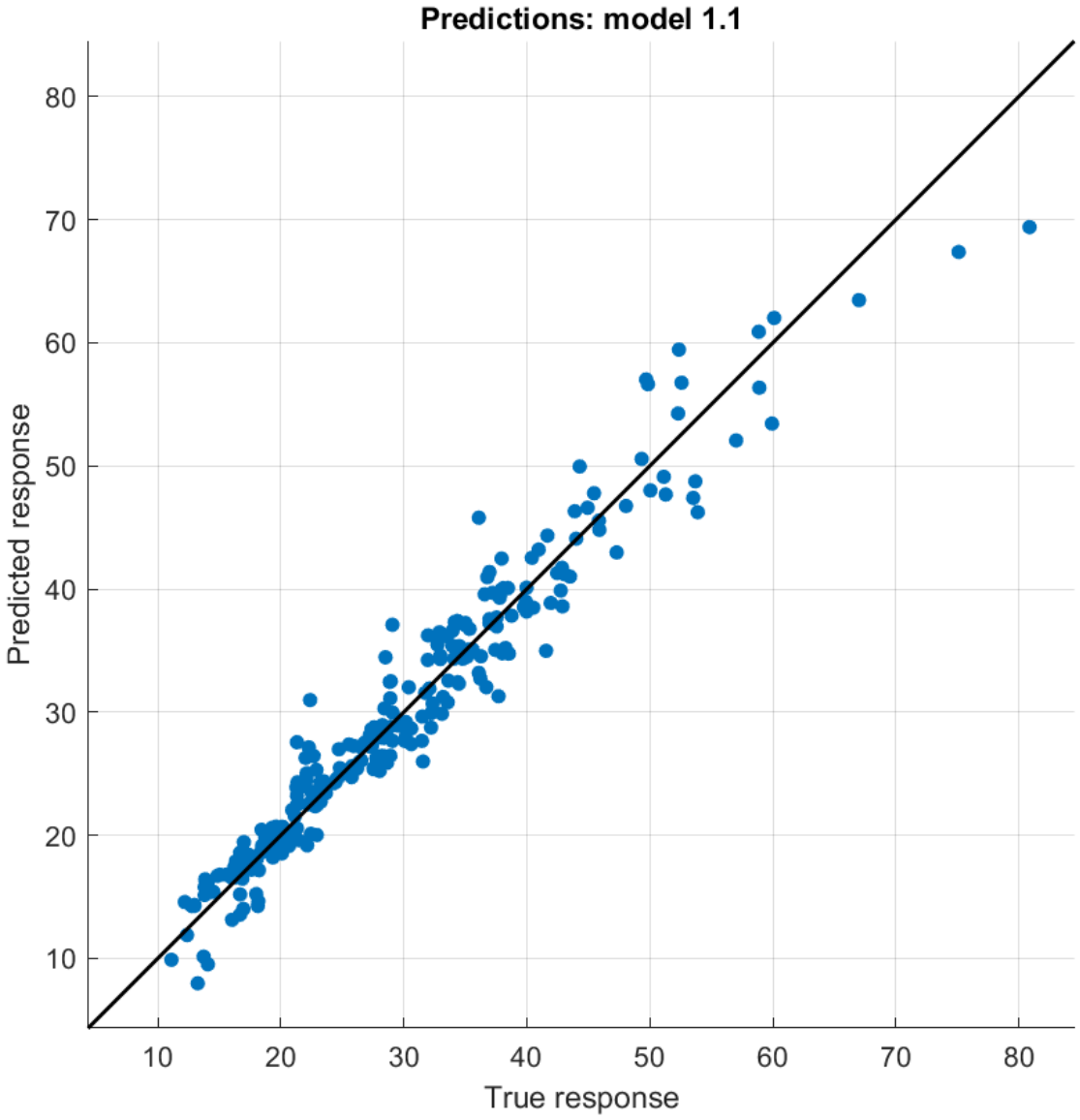


Figure 5.2.1 True vs Predicted for Linear Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive

strength.

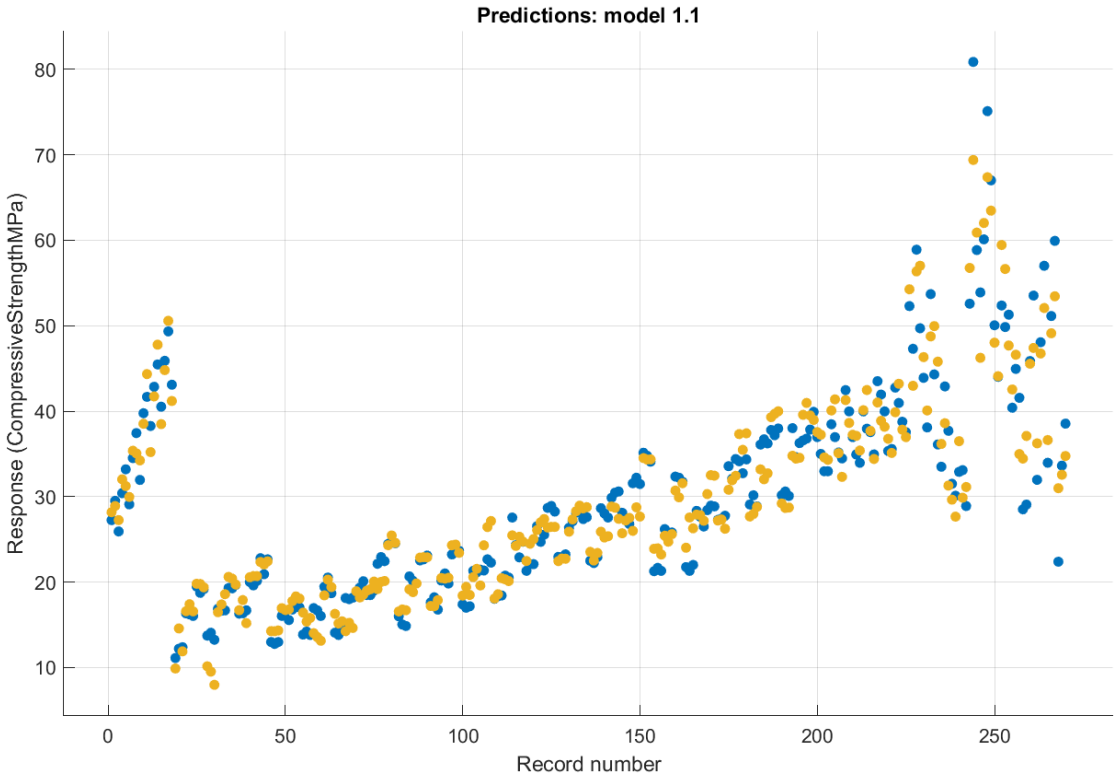


Figure 5.2.2 Response Plot for Linear Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.2.2 Stepwise Quadratic Regression with Interactions

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.2-4 Result by Stepwise Quadratic Regression with Interactions

	Estimate	SE	tStat	pValue
(Intercept)	42.564	17.324	2.4569	0.01471
Cementkgm3	-0.204	0.02026	-10.07	3.49E-20
CoarseAggregateskgm3	-0.15382	0.01442	-10.666	4.58E-22
FineAggregateskgm3	-0.17503	0.01459	-11.994	2.21E-26
CoarseRCAkgm3	-0.17596	0.01506	-11.686	2.29E-25
FineRCAkgm3	-0.17481	0.01541	-11.346	2.95E-24
WaterToBinderRatio	-129.25	13.031	-9.9192	1.03E-19
TotalUnitWeightkgm3	0.15722	0.01624	9.6802	5.64E-19
GraniteFineskgm3	-0.18007	0.01567	-11.49	1.00E-24
FlyAshContentkgm3	-0.17954	0.02016	-8.904	1.24E-16
GroundGranulatedBlast FurnaceSlag GGBSkgm3	-0.15427	0.02065	-7.4725	1.39E-12
NanoSilicakgm3	565.88	114.13	4.9583	1.33E-06
Fillerkgm3	0.088931	0.02007	4.4311	1.41E-05
CrumbRubberkgm3	-0.06443	0.00804	-8.009	4.68E-14
MetakaoliniteContentkgm3	-0.19062	0.01996	-9.5524	1.39E-18
SchmidtReboundNumber	-0.21377	0.16284	-1.3127	1.91E-01
UPVkms	-1.6921	4.1377	-0.409	0.68293
AgeOfConcretedays	0.36197	0.06547	5.529	8.23E-08
CoarseAggregateskgm3: TotalUnitWeightkgm3	-1.12E-05	3.10E-06	-3.6044	3.79E-04

CoarseAggregateskgm3: NanoSilicakgm3	-0.67958	0.1371	-4.9566	1.34E-06
TotalUnitWeightkgm3: UPVkms	0.005257	0.00197	2.6746	7.99E-03
UPVkms: AgeOfConcretedays	-0.05779	0.01606	-3.598	0.00039
WaterToBinderRatio^2	71.851	9.5063	7.5582	8.15E-13
SchmidtReboundNumber^2	0.015259	0.00246	6.2105	2.25E-09
AgeOfConcretedays^2	-0.00093	0.00027	-3.4098	0.00076

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed.

The result from the table shows the different coefficients and the result that they add to the model. A feature labeled as $A{:}\,B$ would add an interaction term $\beta_{AB}x_Ax_B$ to the standard linear equation. In other words, $A{:}\,B$ is an interaction term between A and B.

Table 5.2-5 Model training results

RMSE (Validation)	2.9804

R-Squared (Validation)	0.94
MSE (Validation)	8.8826
MAE (Validation)	1.8726
Prediction speed	~6500 obs/sec
Training time	320.71 sec

Table 5.2-6 Model parameters

Model Type	
Preset	Stepwise Linear
Initial terms	Linear
Upper bound on terms	Quadratic
Maximum number of steps	1000

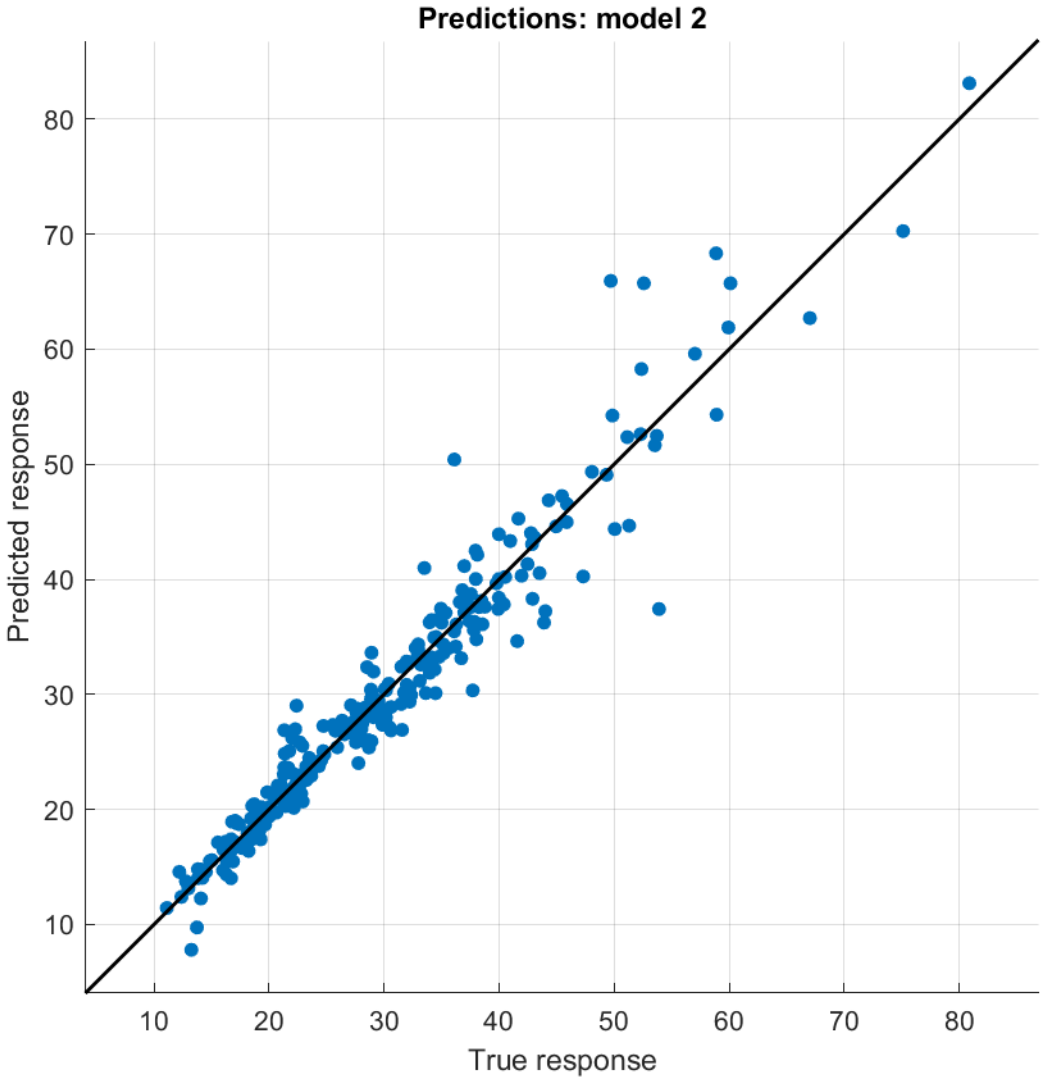


Figure 5.2.3 Predicted vs Actual for Stepwise Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

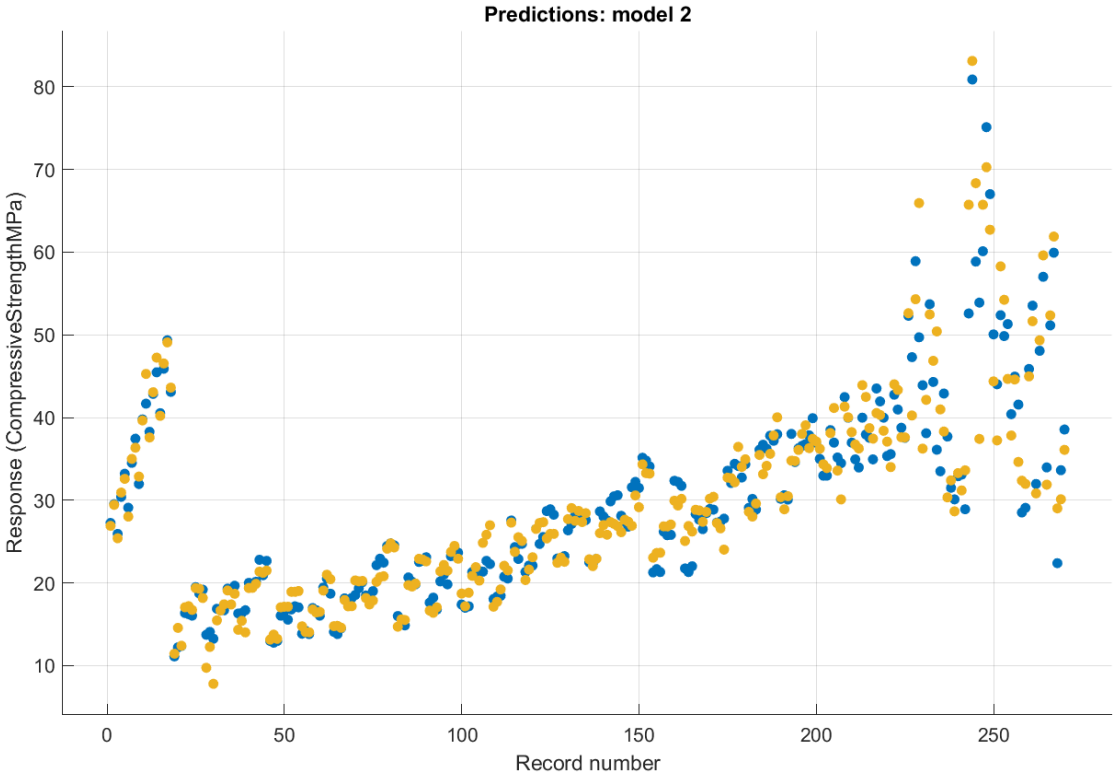


Figure 5.2.4 Response Plot for Stepwise Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.2.3 Exponential Gaussian Process Regression

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.2-7 Model training results

RMSE (Validation)	2.2208
R-Squared (Validation)	0.96
MSE (Validation)	4.9318
MAE (Validation)	1.3123
Prediction speed	~12000 obs/sec
Training time	0.97213 sec

Table 5.2-8 Model parameters

Model Type	
Preset	Exponential GPR
Basis function	Constant
Kernel function	Exponential
Use isotropic kernel	true
Kernel scale	Automatic
Signal standard deviation	Automatic
Sigma	Automatic
Standardize	true
Optimize numeric parameters	true

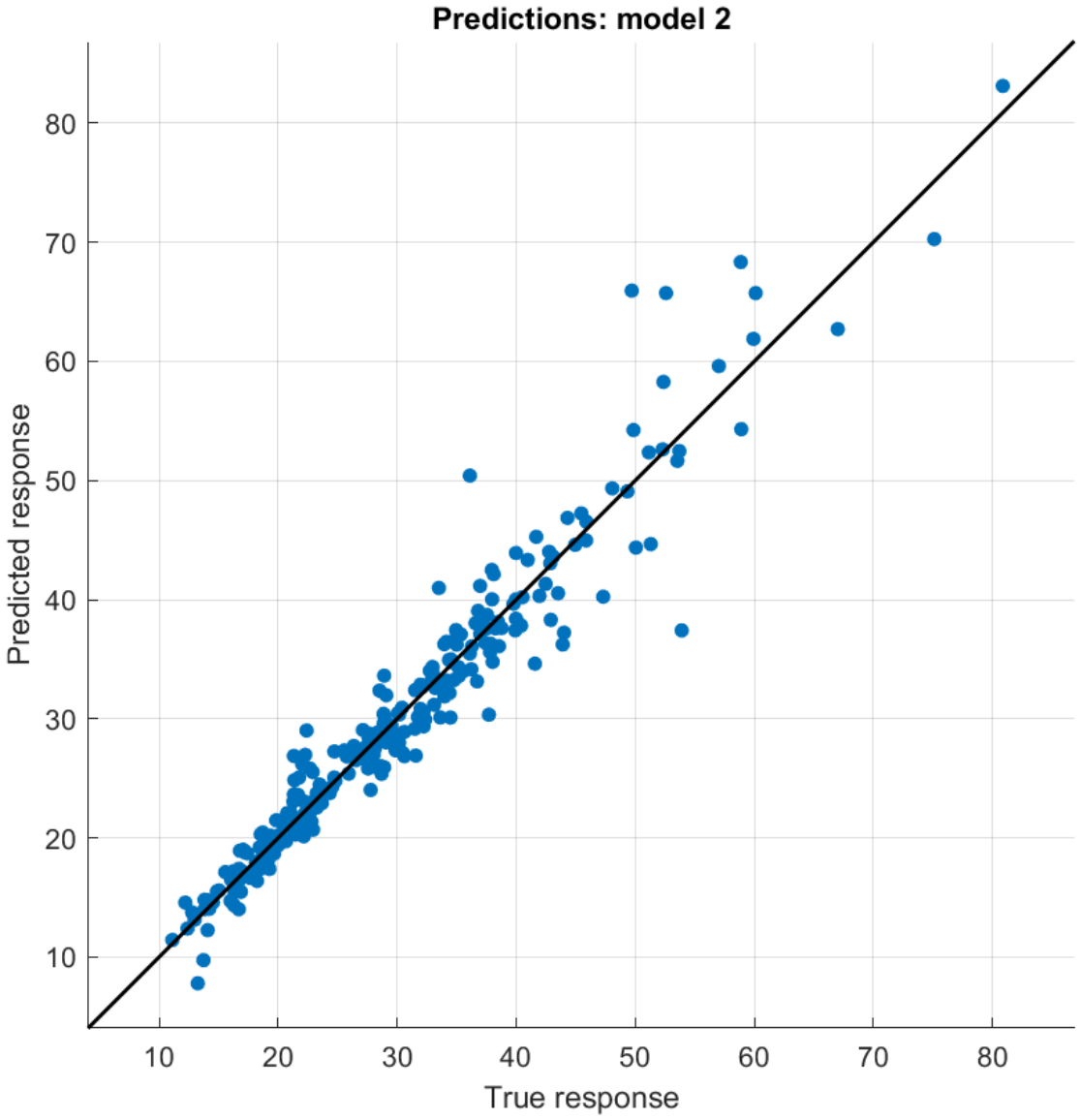


Figure 5.2.5 Predicted vs Actual for Exponential Gaussian Process Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers

and that most of the reliable data is between 10 to 45 MPa compressive strength.

Figure 5.2.6 Response Plot for Exponential Gaussian Process Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.2.4 Untweaked neural network

Table 5.2-9 Model training results

RMSE (Validation)	3.0513

R-Squared (Validation)	0.93
MSE (Validation)	9.3106
MAE (Validation)	1.7819
Prediction speed	~18000 obs/sec
Training time	3.1385 sec

Table 5.2-10 Model parameters

Model Type	
Preset	Bilayered Neural Network
Number of fully connected layers	2
First layer size	10
Second layer size	10
Activation	ReLU
Iteration limit	1000
Regularization strength (Lambda)	0
Standardize data	Yes

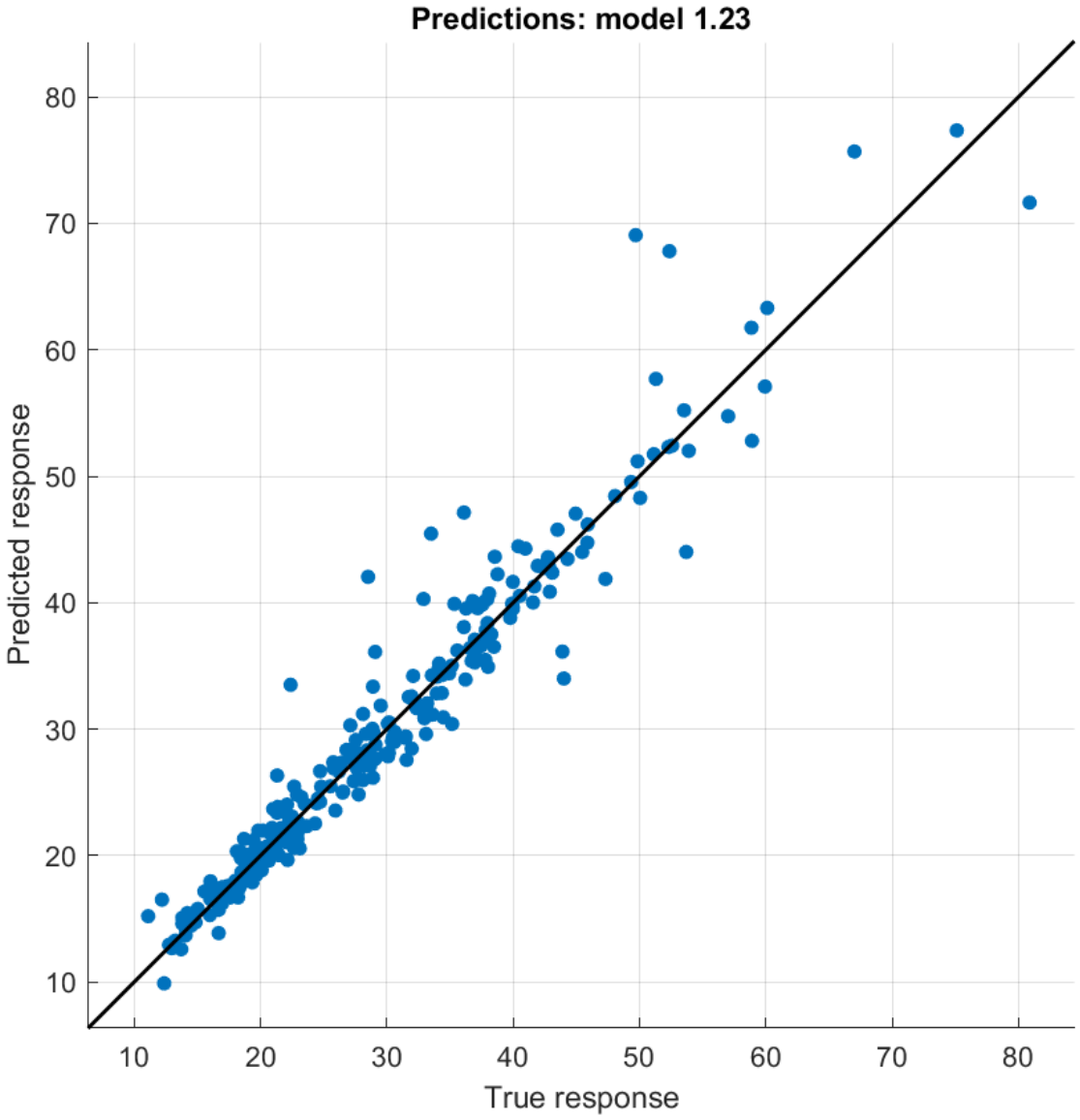


Figure 5.2.7 Predicted vs Actual for Untweaked Neural Network

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive

strength.

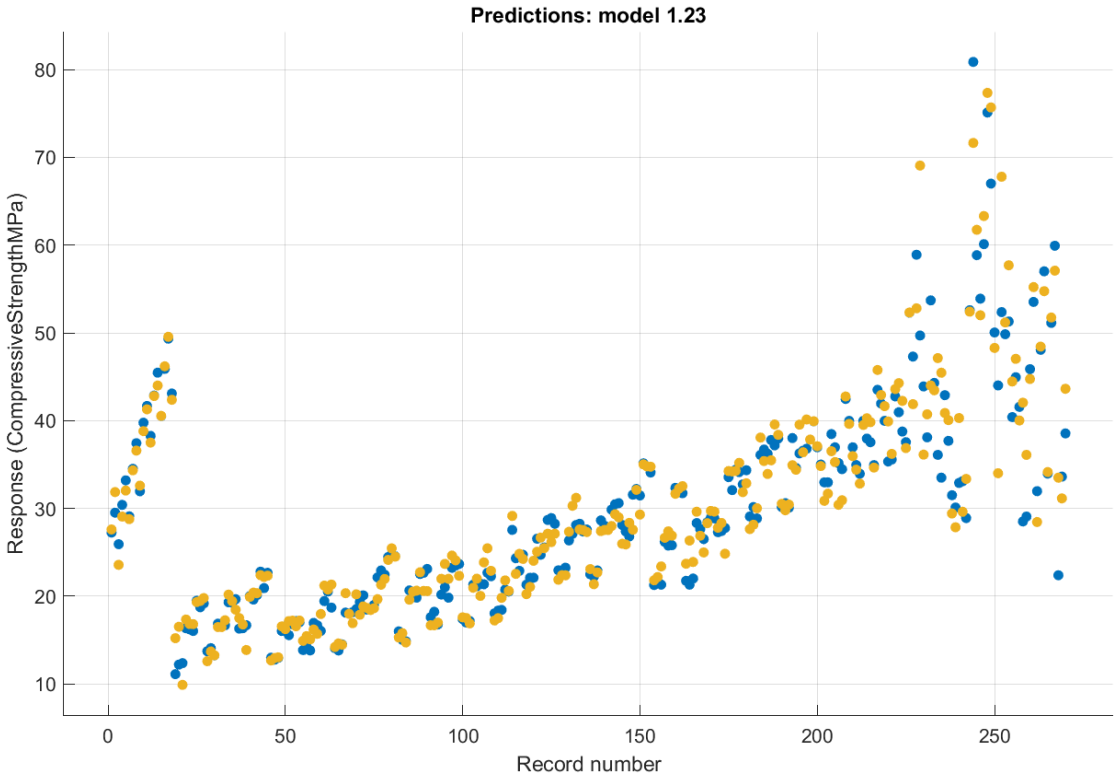


Figure 5.2.8 Response Plot for Untweaked Neural Network

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.2.5 Tweaked neural network

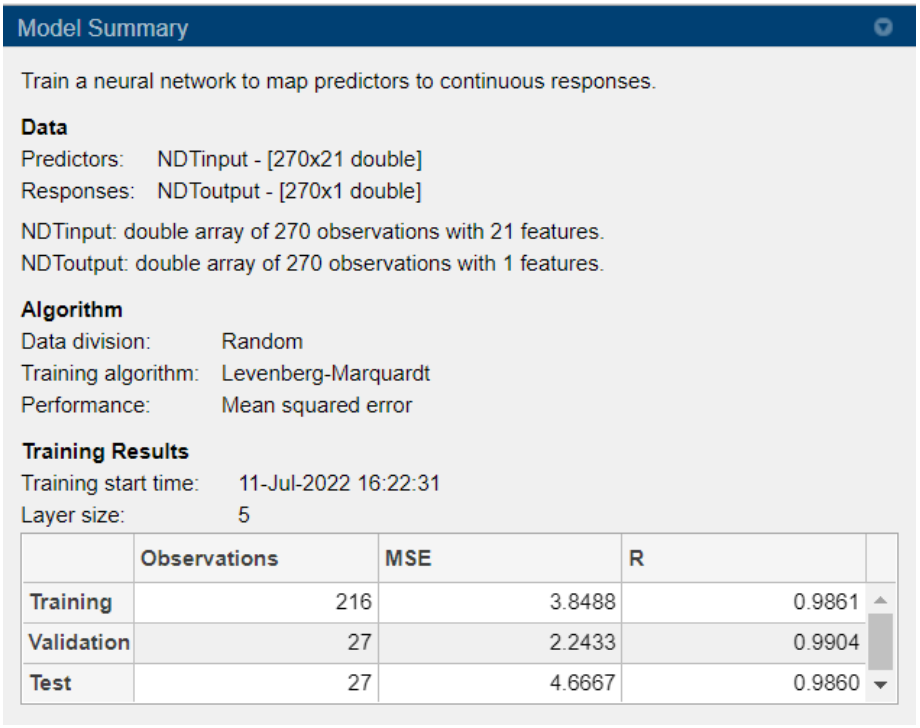


Figure 5.2.9 Model Summary.

The Figure above shows the summary of the model. The R value shown indicates that the model created is a good match to the data given. Moreover, the closeness of the mean square error between training, validation and test means that no overfitting has occurred. The test-train ratio of 80:20 is also implemented. This result is chosen since the mean squared error is lower than the value obtained using other methods, such as stepwise regression.

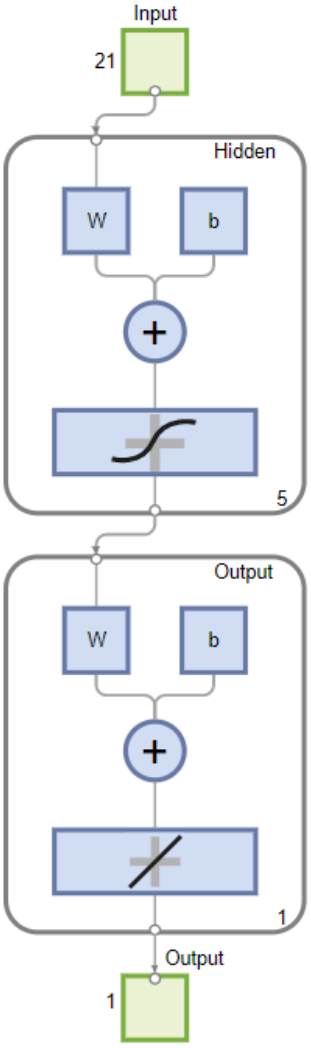


Figure 5.2.10 Diagram of the neural network.

The Figure above shows that a sigmoid activation is used. It also shows that there are 21 features as input and 1 as output. It also shows that the hidden layer has a size of 5.

Training Results

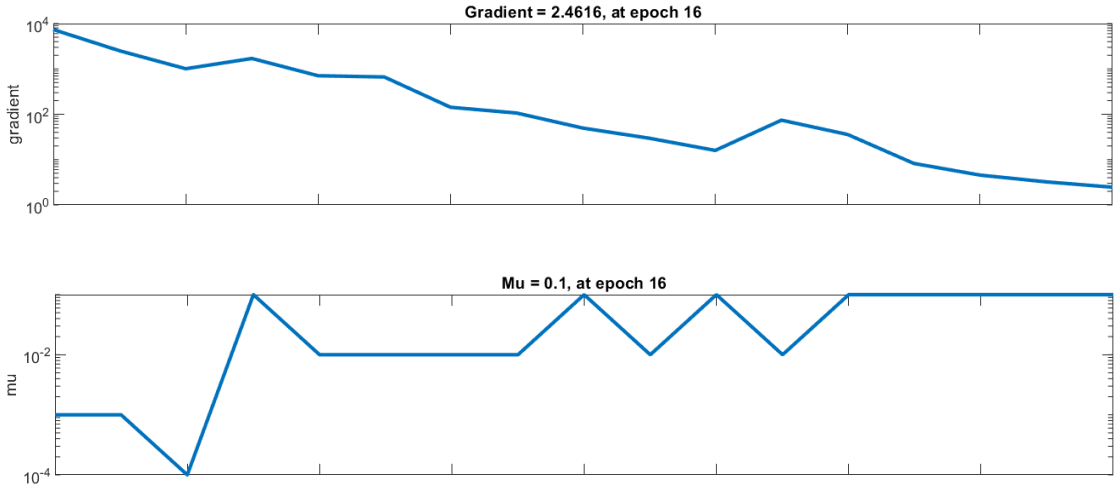
Training finished: Met validation criterion

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	16	1000
Elapsed Time	-	00:00:00	-
Performance	1.78e+03	2.26	0
Gradient	7.39e+03	2.46	1e-07
Mu	0.001	0.1	1e+10
Validation Checks	0	6	6

Figure 5.2.11 Training progress with elapsed time and different stopping criteria

The Figure above shows that the machine learning run is successful. Namely, the mean squared error has decreased. This is shown under performance. The training was finished by meeting the validation criteria, which is that for 6 consecutive iterations, the validation error increases.



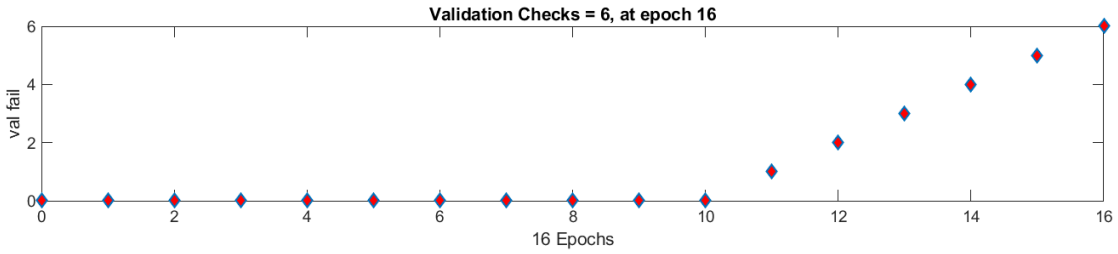


Figure 5.2.12 Different charts showing the various training parameters.

The gradient chart shows that the steps needed to reach the goal gets smaller, which is the expected outcome.

The mu chart measures How close to the newton's method the analysis would be. A high mu would make the algorithm be equivalent to gradient descent with small steps, while a small mu would make the algorithm be closer to newton's method. It is beneficial to get to Newton's method as quickly as possible since it is faster and is more accurate near an error minimum. Thus, mu is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

The validation checks show the accumulated amount of validation checks failed in a row. The chart looks as expected since the six failures of each epoch to increase the performance on the validation test caused the test to be finished.

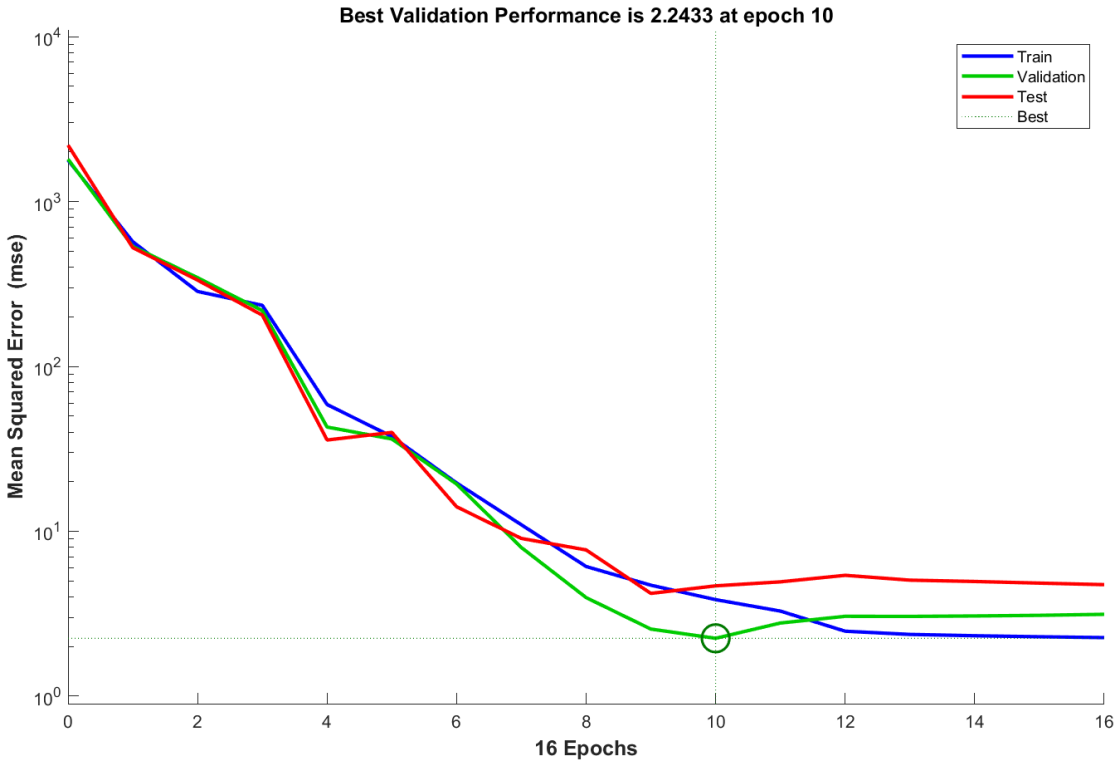


Figure 5.2.13 Performance (Mean squared error) for each of the epochs or train, validation, and test.

The Figure above shows that the neural network is improving. I also show that the best version of the neural network was found on epoch 10.

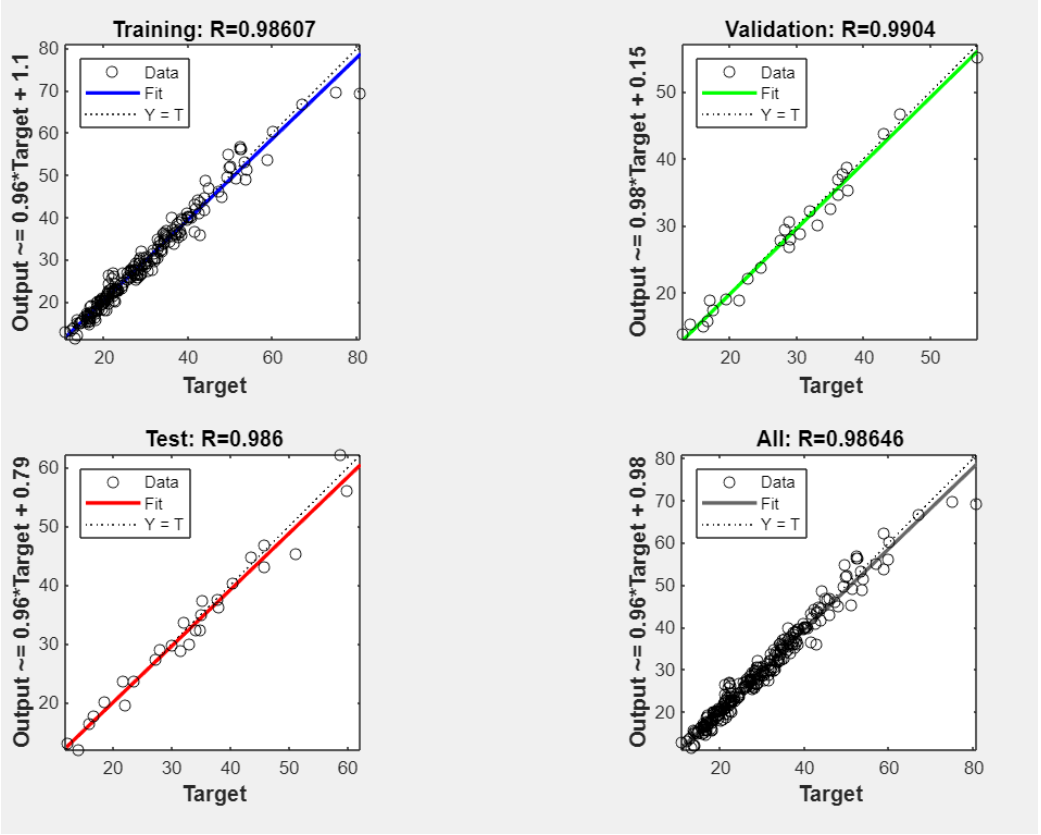


Figure 5.2.14 Charts showing the correlation between the target and the output.

The Figure above shows that the neural network is predicting well. Moreover, it demonstrates that there is much alignment between the output of the neural network and the target value.

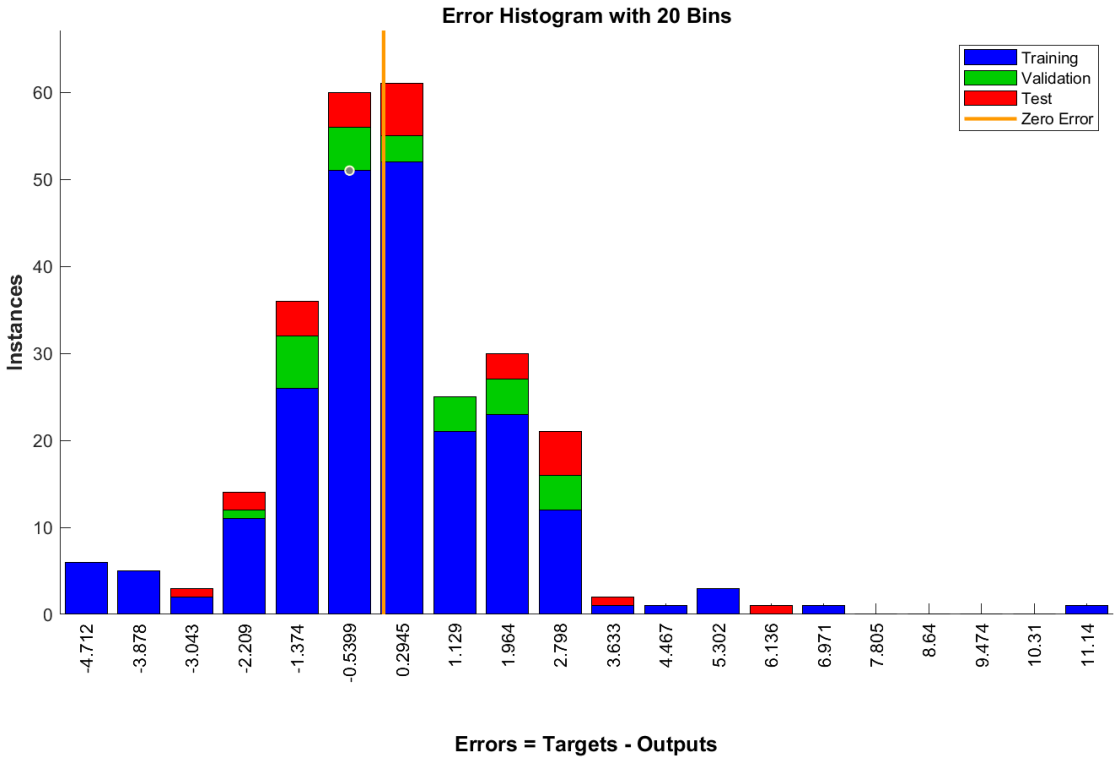


Figure 5.2.15 Error histogram of the neural network.

The error histogram mostly follows the curve expected from the neural network, namely that except for outliers, the errors follow the normal distribution. Nevertheless, the outliers show the blind spots of the model.

5.2.5.1 Comparison between predicted values vs real values

The comparison of predicted values vs real values is used to see to what extent the predictions will align with the real data. The comparison is as follows:

Table 5.2-11 Comparison between real and predicted values when the neural network is applied to the original dataset.

Compressive Strength (Source)	Compressive Strength (Predicted)
27.25	27.10
29.52	30.54
25.93	26.11
30.41	30.80
33.2	33.33
29.1	28.66
34.52	33.79
37.44	36.78
31.96	32.14
39.77	39.50
41.68	43.19
38.27	36.70
42.86	43.55
45.47	46.61
40.53	40.22
45.9	46.79
49.34	49.57
43.1	43.76
11.117673	12.87
12.207564	13.13
12.382182	13.08
16.35327	17.06
16.229664	17.22
16.044255	16.80
19.489527	20.12
18.747891	20.12
19.183455	20.09
13.734	12.07
14.082255	12.02
13.254291	11.48
16.8732	15.59
16.655418	16.00
16.698582	16.74
19.314909	20.34

19.270764	20.16
19.663164	19.62
16.311087	15.21
16.35327	16.46
16.698582	14.75
20.0124	20.17
19.62	20.40
20.142873	20.28
22.802364	22.17
20.927673	22.13
22.671891	22.33
12.992364	13.82
12.774582	13.67
12.98844	13.87
16.044255	16.42
16.568109	16.42
15.565527	16.50
16.792758	18.87
17.178291	19.16
17.047818	18.87
13.864473	15.67
14.213709	15.10
13.821309	14.92
16.960509	16.01
16.698582	15.79
16.044255	15.63
19.445382	18.98
20.535273	20.17
18.704727	19.51
14.082255	15.34
13.821309	14.91
14.5188	14.97
18.137709	15.79
18.006255	16.21
18.180873	15.70
18.530109	20.03
19.358073	19.32
20.099709	19.65

18.485964	17.96
18.485964	18.15
19.009818	18.47
22.149018	19.61
22.933818	20.08
22.454109	20.31
24.459273	23.73
24.808509	24.67
24.546582	24.07
16.001091	14.95
15.03873	15.47
14.867055	15.41
20.666727	18.21
20.142873	18.02
19.837782	18.45
22.541418	22.80
22.671891	22.74
23.107455	22.71
17.61876	17.36
18.225018	17.36
16.785891	17.76
20.187018	20.82
21.014982	21.36
19.837782	20.82
23.238909	23.28
23.499855	23.59
23.674473	22.68
17.396073	17.21
17.003673	17.52
17.178291	17.29
21.320073	19.52
21.145455	20.94
21.451527	18.85
21.364218	24.16
22.671891	26.18
22.279491	26.94
18.0504	17.94
18.355491	18.52

18.4428	19.85
20.753055	21.37
20.535273	21.01
27.555309	27.87
24.3288	23.28
22.900464	24.30
24.7212	23.76
21.320073	20.71
22.10193	22.51
22.104873	23.26
26.552727	25.91
24.7212	26.84
25.549164	26.98
28.688364	26.61
28.907127	26.61
28.2528	26.61
22.9554	22.42
22.933818	22.93
23.2497	22.80
26.35947	27.25
27.118764	28.43
28.122327	28.96
28.2528	27.69
27.380691	27.25
27.598473	27.46
22.497273	22.40
22.236327	21.48
22.933818	22.40
28.6452	26.42
28.035018	25.92
27.555309	26.34
29.865564	28.85
30.476727	28.73
30.6072	27.49
28.122327	25.83
27.380691	26.68
26.813673	27.42
31.566618	27.54

32.219964	30.17
31.479309	28.88
35.141382	32.54
34.793127	32.32
34.094655	32.25
21.276909	22.70
21.669309	22.83
21.320073	22.09
26.203491	25.85
25.767927	25.35
25.811091	25.98
32.351418	30.50
32.219964	29.78
31.740255	31.41
21.756618	23.70
21.320073	26.40
22.017564	25.62
28.340109	29.46
27.642618	29.31
26.508582	27.75
28.427418	29.07
28.950291	30.55
28.862982	30.55
27.293382	27.73
27.423855	27.53
27.773091	25.33
33.571782	33.45
32.089491	33.63
34.400727	34.79
34.1388	36.02
32.743818	34.77
34.356582	36.31
29.080764	27.89
30.159864	28.41
28.862982	29.09
36.1008	35.62
36.710982	33.94
36.231273	34.61

37.800873	35.37
37.190691	35.90
37.975491	36.28
30.170655	29.88
30.6072	29.30
30.084327	29.30
38.018655	36.21
34.618509	35.79
36.275418	36.95
36.580509	37.20
36.798291	37.77
37.845018	37.58
39.92277992	40.99
36.96911197	37.10
35	35.00
32.97297297	30.58
32.97297297	29.88
38.47490347	36.01
36.96911197	36.32
35.17374517	35.26
34.47876448	34.26
42.47104247	44.16
39.98069498	39.95
36.96911197	37.17
34.94208494	35.54
33.95752896	32.65
39.98069498	40.24
37.95366795	38.87
37.54826255	38.37
34.94208494	36.94
43.51351351	44.76
41.94980695	42.18
39.98069498	39.99
35.34749035	37.36
35.57915058	34.21
42.76061776	41.01
40.96525097	39.92
38.76447876	39.53

37.54826255	38.75
52.30252596	56.35
47.3033537	46.15
58.90143334	53.73
49.70295638	54.83
43.90391656	41.73
38.10487674	39.09
53.70229419	49.00
44.30385034	48.69
36.10520784	39.96
33.50563827	34.22
42.90408211	35.96
37.70494296	35.30
31.50596936	30.09
30.10620113	29.68
32.90573759	32.63
33.10570448	30.15
28.90639979	26.84
52.58	56.34
80.87	69.31
58.86	62.20
53.9	51.44
60.11	60.33
75.11	69.77
67.01	66.79
50.05	52.14
44.02	44.64
52.37	56.80
49.85	51.87
51.3	49.29
40.41	40.24
44.95	46.85
41.57	36.62
28.52	29.89
29.08	32.14
45.87	43.02
53.53	53.18
31.97	32.23

48.07	44.94
57.02	55.16
33.97	32.02
51.14	45.31
59.93	56.03
22.39	26.73
33.63	32.17
38.55	39.75

It could be seen that there are some differences between the real value and the predicted value.

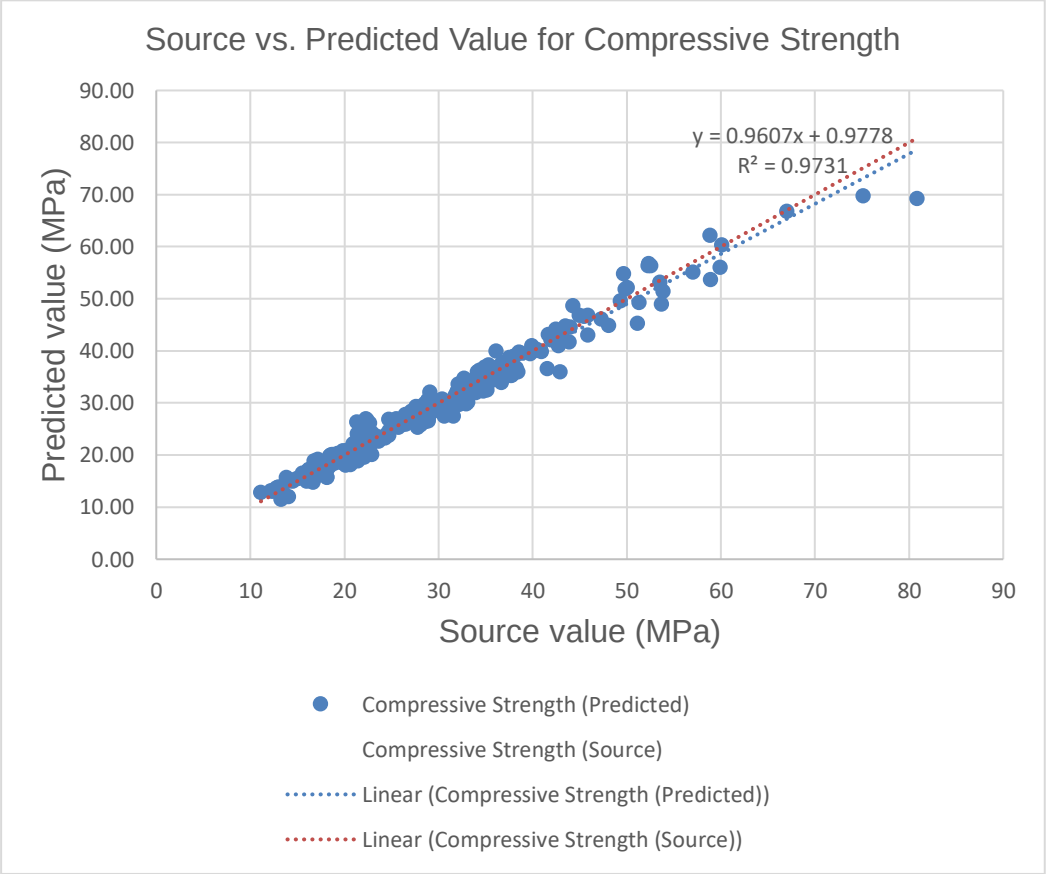


Figure 5.2.16 Source vs. Predicted Value for Compressive Strength

The chart would confirm the extent of similarity between the

source value and the predicted value. The comparison between the y=x trendline also highlights the difference between the real and predicted values. The graph also shows the areas where the outliers are.

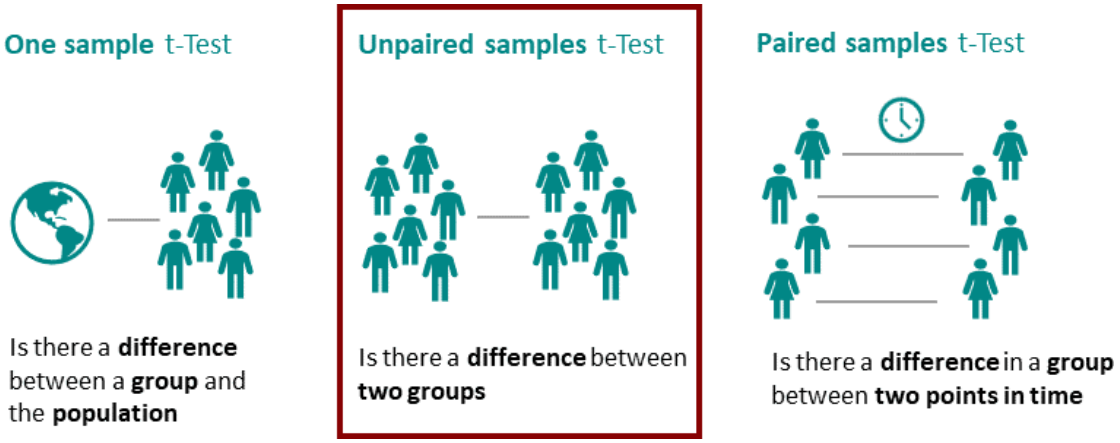


Figure 5.2.17 Different kinds of t-test (DATAtab Team, 2022)

From the figure above it can be seen that an unpaired samples t-test would be the t-test that would be most appropriate when looking at the difference between two groups. We are eager to see the difference between the real values and the values from the model to determine if the model is sufficiently similar.

Table 5.2-12 Comparison between real and predicted values when the neural network is applied to the original dataset.

	Compressive Strength (Source)	*Compressive Strength (Predicted)*
Mean	29.41937114	29.24153998
Variance	138.6808975	131.5377093
Observations	270	270
Hypothesized Mean Difference	0	
df	538	
t Stat	0.177759205	
P(T<=t) one-tail	0.429489497	
t Critical one-tail	1.647690825	
P(T<=t) two-tail	0.858978995	
t Critical two-tail	1.964383179	

From the table above, the P(T<=t) is greater than 0.05 for both one-tail and two-tail. This would indicate that the predictions are sufficiently similar with the real values. The predictions, however, are only sufficiently accurate for the 10-60 MPa range. This could be seen as the values above 60 MPa are scarce.

5.2.5.2 Tweaked neural network code

```
function [Y,Xf,Af] = NDTNNet2coder(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 11-Jul-2022 21:08:33.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = 21xQ matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%
```

% where Q is number of samples (or series) and TS is the number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 18 19 20 21];
x1_step2.xoffset =
[0;0;0;0;0;35;0.1;1285.5;0;0;0;0;0;0;0;0;14;2.93890080756283;7];
x1_step2.gain =
[0.00389105058365759;0.0015503875968992;0.0017389792191983;0.003
06748466257669;0.0024390243902439;0.00826446280991736;2.898550724
63768;0.0017785682525566;0.0060716454159077;0.004;0.009779951100
2445;0.248138957816377;0.0192492781520693;0.00579206487112656;0.00
4;0.571428571428571;0.0526868947757209;0.869905920796697;0.0240963
855421687];
x1_step2.ymin = -1;

% Layer 1
b1 = [-2.9114928109822271196;1.0605029505100838083;-
0.79305235122293715744;-
1.6849369035147185869;2.5497005479479368795];
IW1_1 = [-0.36521660578107323358 -1.7908717578888597721 -
1.6976213180738470854 -1.1314783627817295297 -
1.1285059216473585231 0.10736070196759561757 -
0.32809957575717074718 1.1695300291137042947 -
0.63744051638111887126 -0.50168888359831331769 -
0.3757235235535827389 0.17891227807019860485 -
0.005126992079895600906 0.15712226737440698754 -
0.50071083909786329169 0.97795892887253388359
0.60040494135135169529 0.79017646355612081166
0.071411188280547363560;-0.94962302152461519622 -
1.851365604096685491 -0.20865229728945552945 -
0.1225944102763181498 -2.2080833507565360563
0.27863626072012587231 0.45636873011938600131 -
0.52954400956060931893 -0.99263653077281888137 -
1.1902671952349253015 -1.6002441707399663873 -
1.6366836624512413056 -0.59521006730462300283
1.8655631310795446343 -0.65296021590202413254
1.0975522786962528254 2.1035758386240241968
4.0396743979728917395 -4.723542786624203238;2.3448092612006949942
2.2588418090303652441 0.082823110421909942880
0.068734407347494391738 2.385176983974686582 -

```
1.6887467159487292712 -0.60762903934141265783 -
4.563366184729527042 -3.0248955399863204363 1.860677104937902282 -
5.2685481755096299494 -1.37920128656186191660.39083660531367048208 1.8546075819441658616
0.672661449240995690250.72885222224803780655 -
0.081444732517545304074 -0.749503917075805325960.029419666739508562592;1.0649803353098585834
1.7878886806841527424 0.58790732723916927505
1.1091732545856720638 -1.1884384534897167729
1.1996895463271515236 2.0386218958500452736
0.18327487829565505817 0.84010458463405723872 -
2.1656836891612170071 1.0040752067982503526 -1.829281839494944828
0.690673736558576223390 -0.614563116383051388780 -
1.608721992302377668 -0.004621251441123994802
0.23383216587691454946 -1.9443343435189333057 -
1.8433976026778366997;3.5747660475842213401 -
1.4819499879069830683 -0.049343257631359556392 -
1.1824196720745629996 -1.0957426845924105319 -
0.308589578966610322830.72462657256890727897
0.50446171278721241293 2.0809048590192631423 -
4.0081646201526641704 3.0992288402615422171
2.9178292341778053753 -5.32329707855320233280
1.1027488226276622729 0.856937856834886546590
2.7504348234559667929 -1.283506343762081725
0.516283811803052272720 -0.0469365117151949451380];

% Layer 2
b2 = -0.084394907777617642064;
LW2_1 = [0.61817754109121691997 -0.073003225366260193763 -
0.16737087685067597587 0.15239569631226507207 -
0.250234938107173454650];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0286728785406686;
y1_step1.xoffset = 11.117673;

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
    X = {X};
end
```

```
% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},2); % samples/series
else
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

    % Input 1
    temp = removeconstantrows_apply(X{1,ts},x1_step1);
    Xp1 = mapminmax_apply(temp,x1_step2);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
```

```
end

% Remove Constants Input Processing Function
function y = removeconstantrows_apply(x,settings)
y = x(settings.keep,:);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

5.3 Destructive Factors

5.3.1 Linear Regression

Linear regression is used here since it is the most intuitive method by which a data analysis could be understood. Linear regression is of form $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$, which makes it very intuitive to understand and use.

Table 5.3-1 Result using linear regression. The values in yellow are the ones that are deemed not significant.

	Estimate	SE	tStat	pValue
(Intercept)	-5.949	51.492	-0.1155	0.90816
Cementkgm3	-0.0071836	0.1829	-0.0393	0.96871
CoarseAggregateskgm3	-0.29254	0.0468	-6.2509	3.28E-09
FineAggregateskgm3	-0.19881	0.0545	-3.6493	0.00035

CoarseRCAkgm3	-0.29672	0.0468	-6.3449	2.01E-09
FineRCAkgm3	0	0	NaN	NaN
WaterContentkgm3	-0.39942	0.3878	-1.0299	0.30455
WaterToBinderRatio	193.11	87.688	2.2023	0.02902
TotalUnitWeightkgm3	0.18636	0.0437	4.2684	3.29E-05
GraniteFineskgm3	0	0	NaN	NaN
FlyAshContentkgm3	-0.17033	0.2046	-0.8327	0.4062
GroundGranulatedBlast FurnaceSlagGGBSkgm3	0	0	NaN	NaN
NanoSilicakgm3	-0.55449	0.2121	-2.6138	0.00977
Fillerkgm3	0.52875	0.3317	1.5941	0.1128
CrumbRubberkgm3	-0.15206	0.0383	-3.9741	0.0001
MetakaoliniteContentkgm3	0	0	NaN	NaN
polypropyleneFibreByVolume	15.333	10.357	1.4803	0.14067
dryCuring	-2.5802	0.8802	-2.9313	0.00385
Superplasticizer	26	23.311	1.1153	0.26632
SchmidtReboundNumber	0	0	NaN	NaN
UPVkms	0	0	NaN	NaN
AgeOfConcretedays	0.33389	0.0206	16.235	3.53E-36

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed. The result from the linear regression shows the importance of each of the variables and coefficient that they would add to the model. The NaN would indicate factors that do not exist within the dataset.

Table 5.3-2 Model training results

RMSE (Validation)	4.5673
R-Squared (Validation)	0.83
MSE (Validation)	20.86
MAE (Validation)	3.3412
Prediction speed	~2200 obs/sec
Training time	11.338 sec

Table 5.3-3 Model parameters

Model Type	
Preset	Linear
Terms	Linear
Robust option	Off

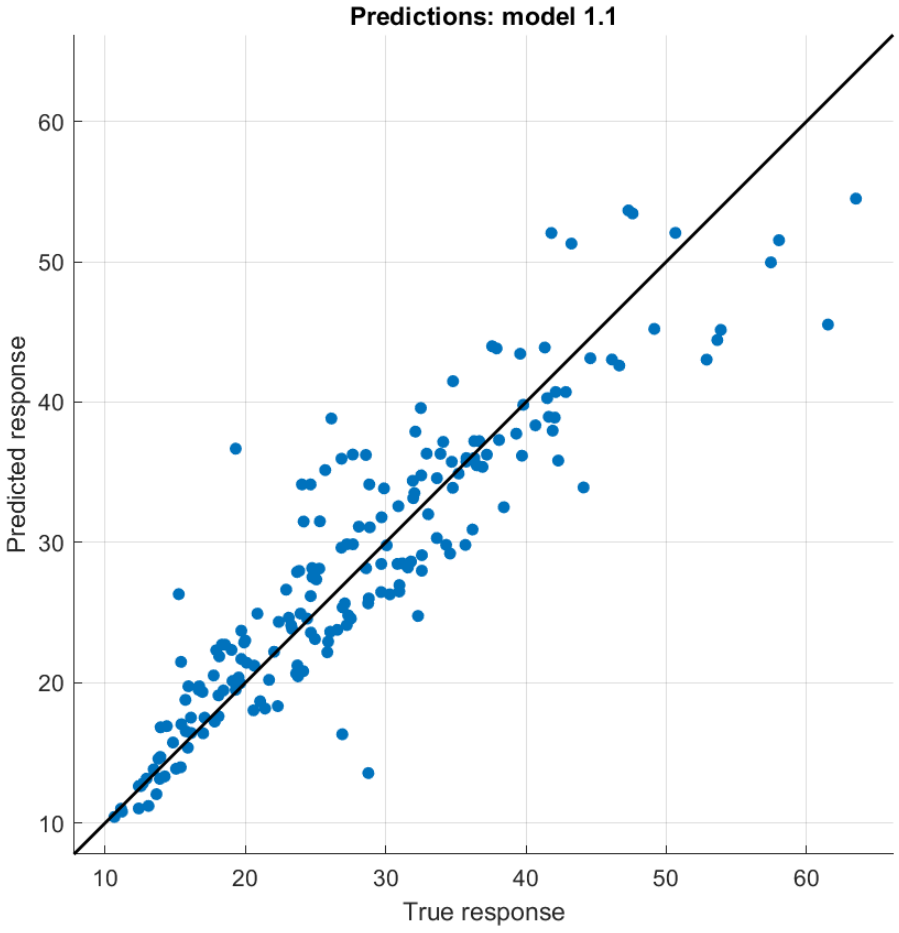


Figure 5.3.1 True vs Predicted for Linear Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

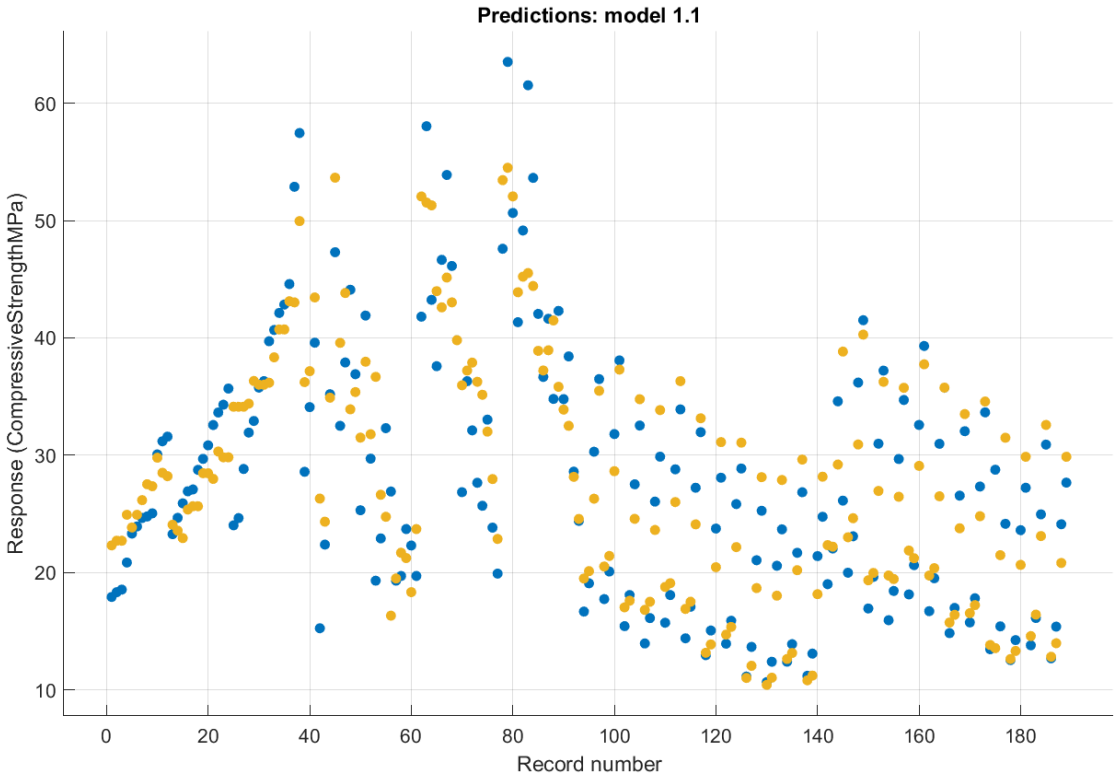


Figure 5.3.2 Response Plot for Linear Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.3.2 Rational Quadratic Gaussian Process Regression

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.3-4 Model training results

RMSE (Validation)	4.5673

RMSE (Validation)	3.6875
R-Squared (Validation)	0.89
MSE (Validation)	13.598
MAE (Validation)	2.3009
Prediction speed	~5800 obs/sec

Table 5.3-5 Model parameters

Model Type	
Preset	Rational Quadratic GPR
Basis function	Constant
Kernel function	Rational Quadratic
Use isotropic kernel	true
Kernel scale	Automatic
Signal standard deviation	Automatic
Sigma	Automatic
Standardize	true
Optimize numeric parameters	true

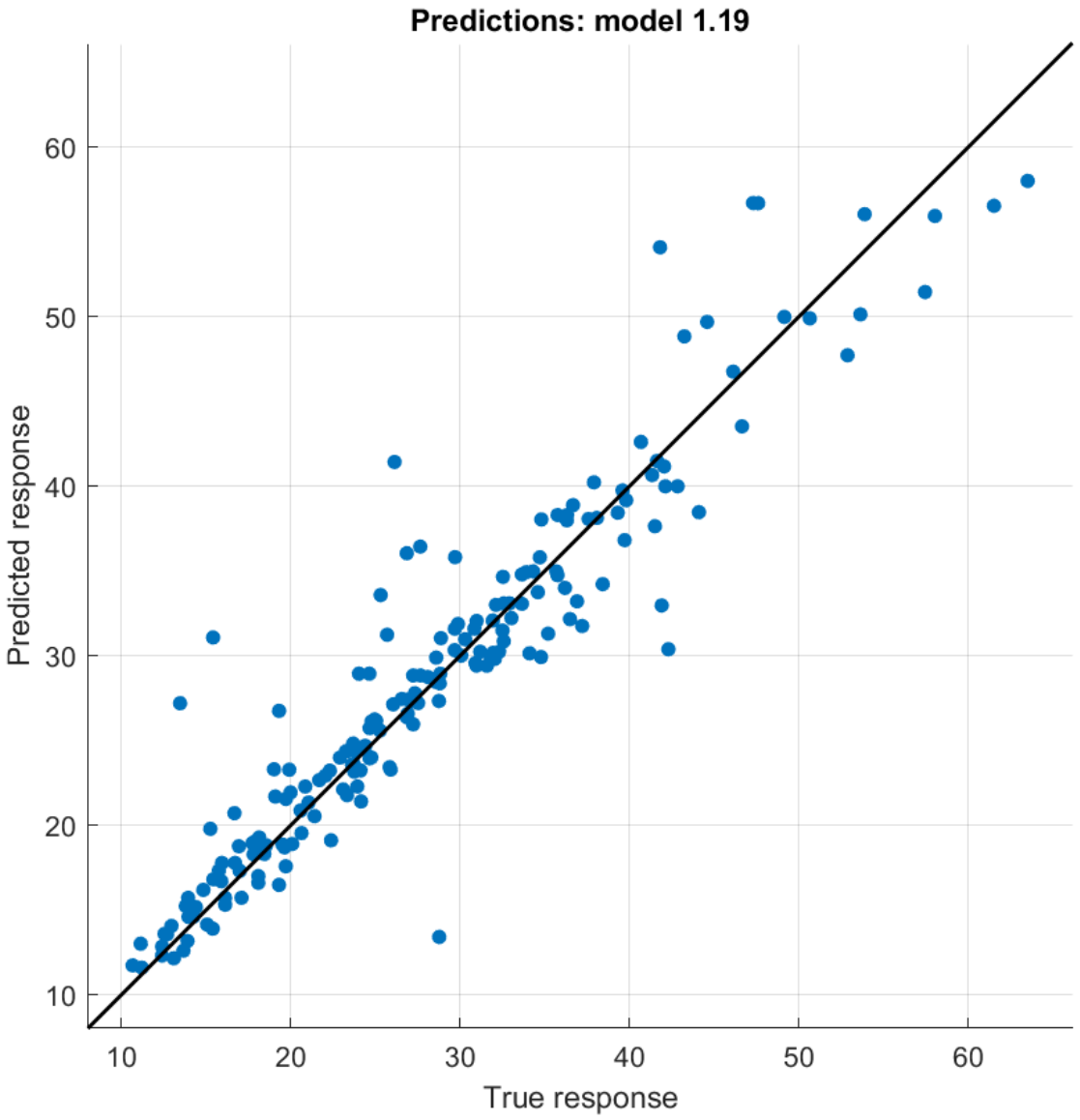


Figure 5.3.3 Predicted vs Actual for Rational Quadratic Gaussian Process Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers

and that most of the reliable data is between 10 to 45 MPa compressive strength.

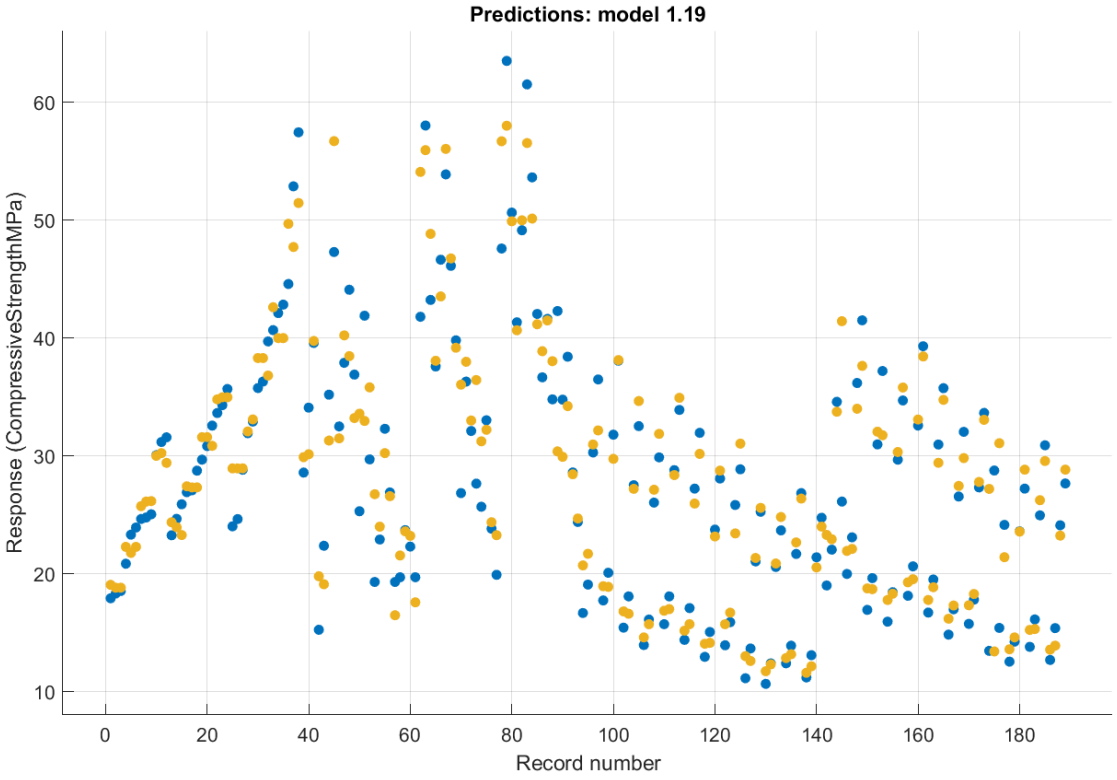


Figure 5.3.4 Response Plot for Rational Quadratic Gaussian Process Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.3.3 Tweaked neural network for destructive testing factors only

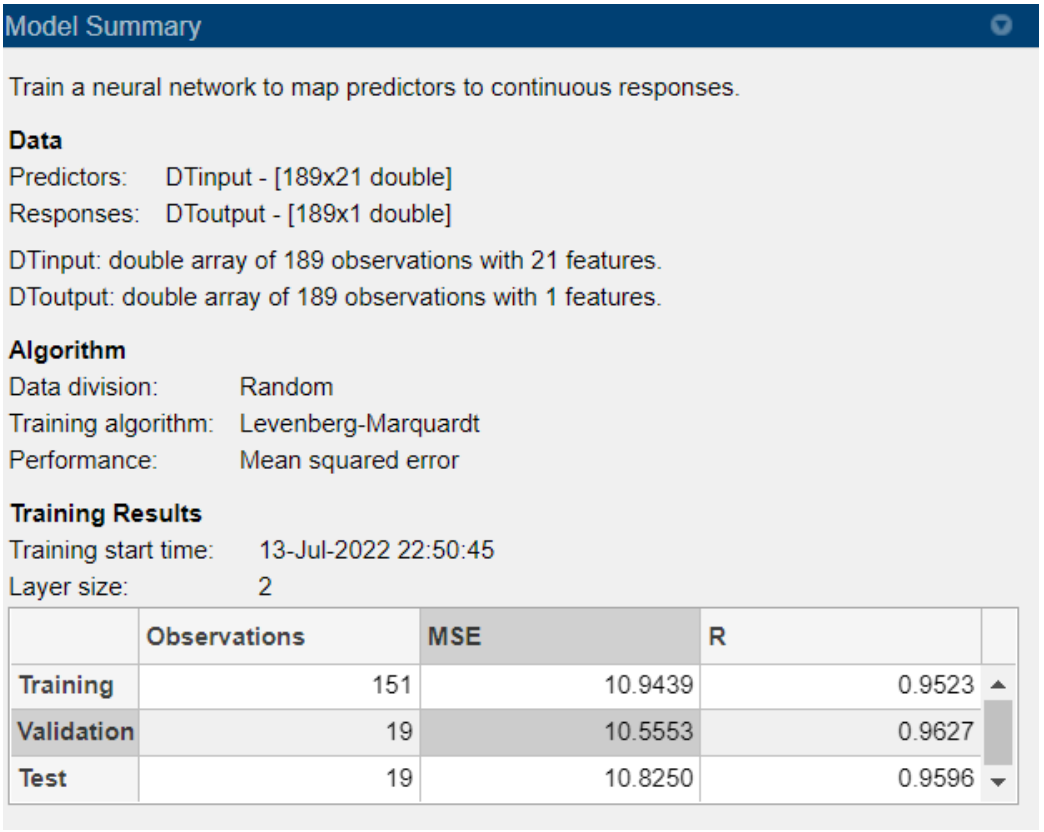


Figure 5.3.5 Model Summary.

The Figure above shows the summary of the model. The R value shown indicates that the model created is a good match to the data given. Moreover, the closeness of the mean square error between training, validation and test means that no overfitting has occurred. The test-train ratio of 80:20 is also implemented. This result is chosen since the mean squared error is lower than the value obtained using other methods, such as stepwise regression.

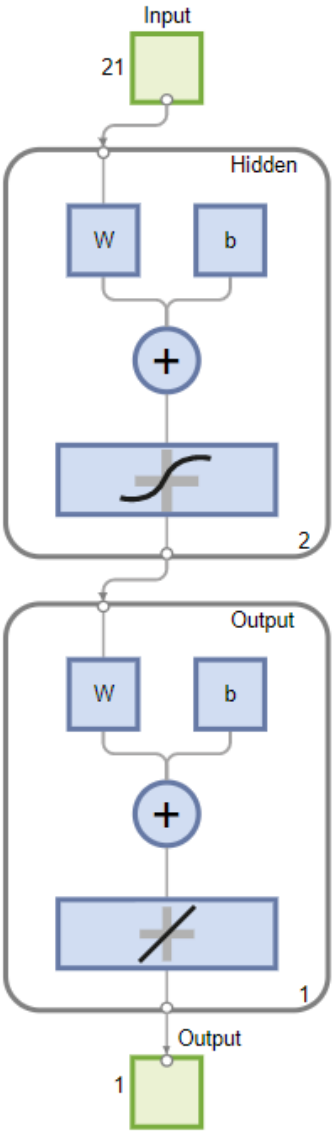


Figure 5.3.6 Diagram of the neural network.

The Figure above shows that a sigmoid activation is used. It also shows that there are 21 features as input and 1 as output. It also shows that the hidden layer has a size of 2.

Training Results

Training finished: Met validation criterion

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	24	1000
Elapsed Time	-	00:00:00	-
Performance	116	10.8	0
Gradient	436	3.55	1e-07
Mu	0.001	0.01	1e+10
Validation Checks	0	6	6

Figure 5.3.7 Training progress with elapsed time and different stopping criteria

The Figure above shows that the machine learning run is successful. Namely, the mean squared error has decreased. This is shown under performance. The training was finished by meeting the validation criteria, which is that for 6 consecutive iterations, the validation error increases.

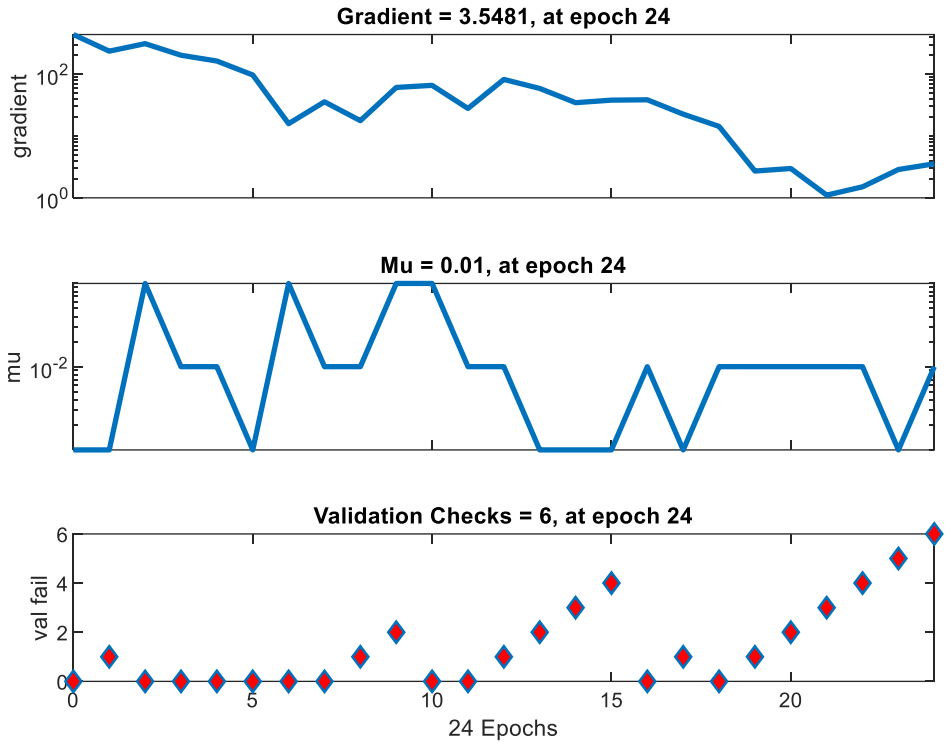


Figure 5.3.8 Different charts showing the various training parameters.

The gradient chart shows that the steps needed to reach the goal gets smaller, which is the expected outcome.

The mu chart measures How close to the newton's method the analysis would be. A high mu would make the algorithm be equivalent to gradient descent with small steps, while a small mu would make the algorithm be closer to newton's method. It is beneficial to get to Newton's method as quickly as possible since it is faster and is more accurate near an error minimum. Thus, mu is decreased after each successful step (reduction in performance function) and is increased

only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

The validation checks show the accumulated amount of validation checks failed in a row. The chart looks as expected since the six failures of each epoch to increase the performance on the validation test caused the test to be finished.

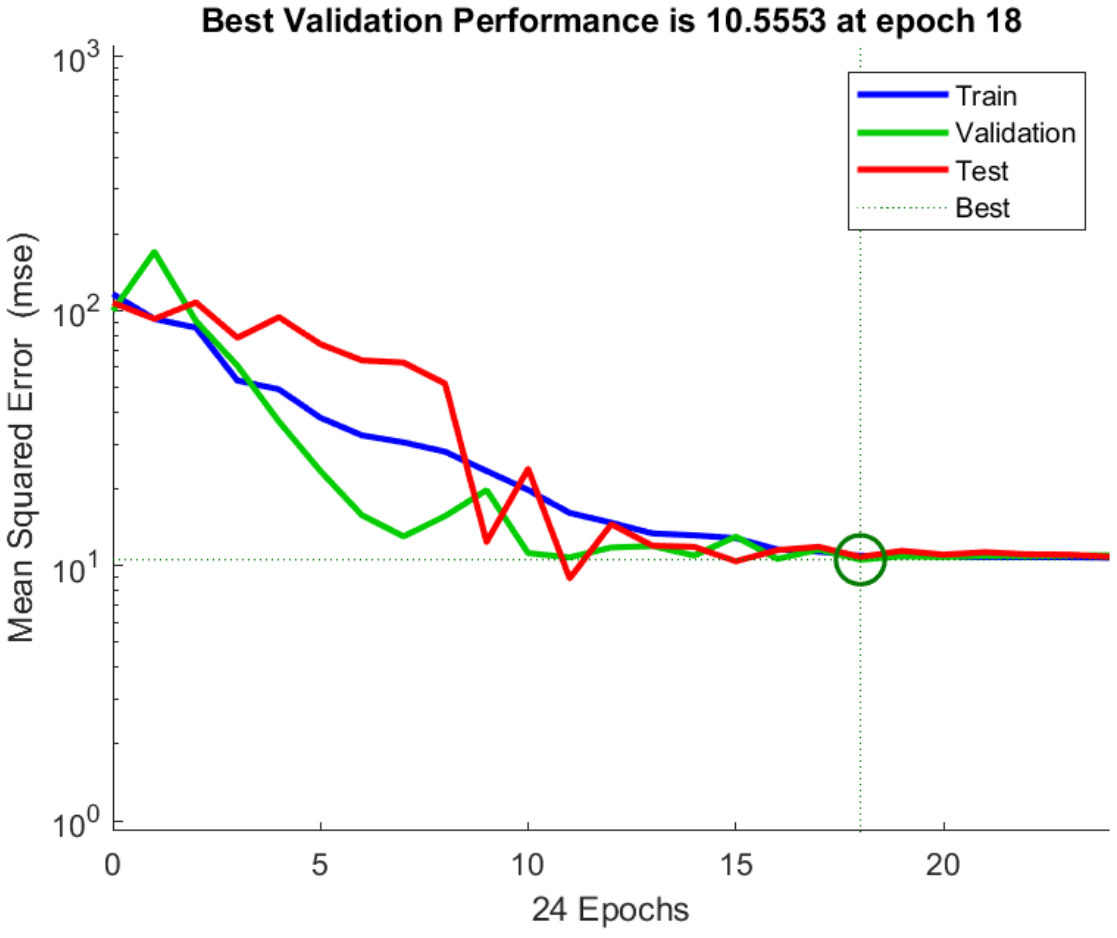


Figure 5.3.9 Performance (Mean squared error) for each of the epochs or

train, validation, and test.

The Figure above shows that the neural network is improving. I also show that the best version of the neural network was found on epoch 18.

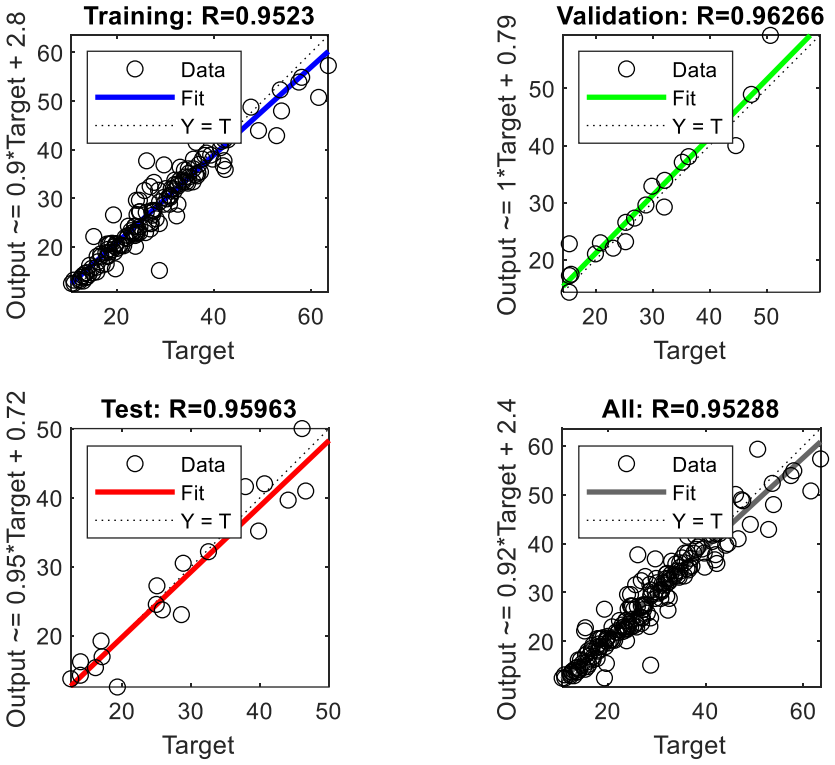


Figure 5.3.10 Charts showing the correlation between the target and the output.

The Figure above shows that the neural network is predicting well. Moreover, it demonstrates that there is much alignment between the output of the neural network and the target value.

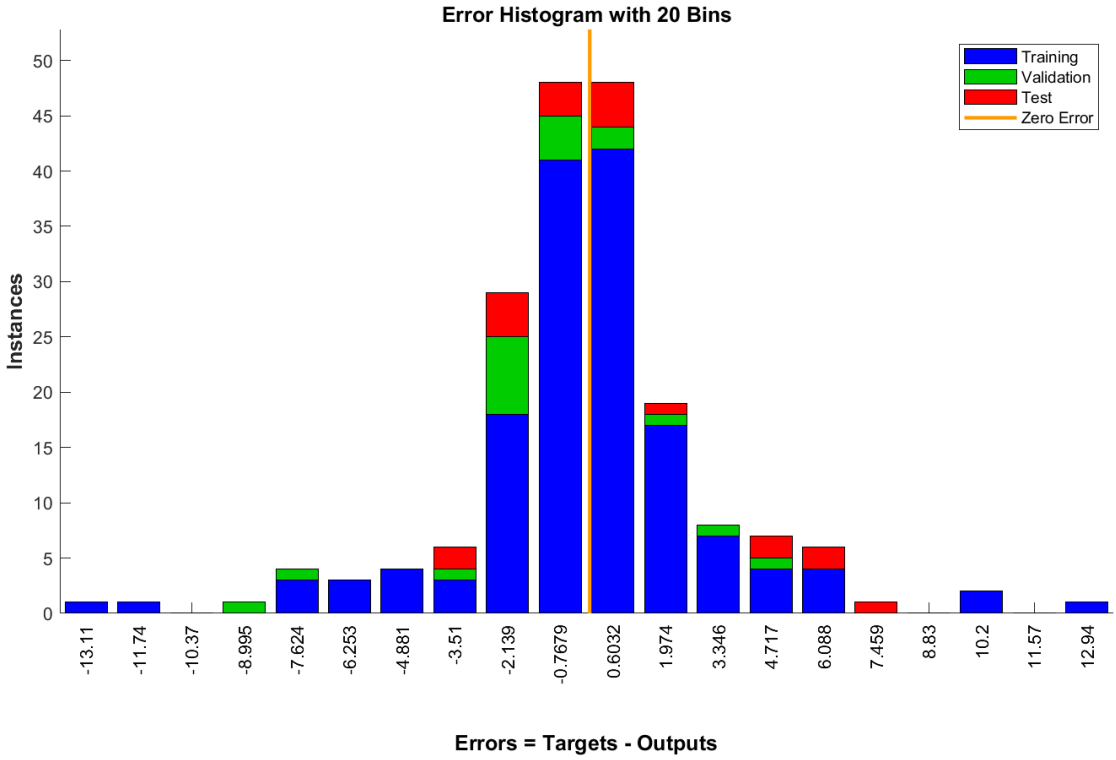


Figure 5.3.11 Error histogram of the neural network.

The error histogram mostly follows the curve expected from the neural network, namely that except for outliers, the errors follow the normal distribution. Nevertheless, the outliers show the blind spots of the model.

5.3.3.1 Comparison between predicted values vs real values

The comparison of predicted values vs real values is used to see to what extent the predictions will align with the real data. The

comparison is as follows:

Table 5.3-6 Comparison between real and predicted values when the neural network is applied to the original dataset.

Compressive Strength (Source)	Compressive Strength (Predicted)
17.92155855	20.57
18.3254812	20.57
18.54422754	20.57
20.8558458	22.96
23.32262387	22.96
23.9292315	22.96
24.65347537	27.22
24.77819508	27.22
25.05006746	27.22
30.07010786	31.98
31.18801294	31.98
31.5817028	31.98
23.26824437	22.93
24.66417555	22.93
25.89965488	22.93
26.92654678	24.79
27.0824143	24.79
28.75111365	24.79
29.68631878	28.77
30.84157217	28.77
32.57445226	28.77
33.64413133	33.38
34.30733235	33.38
35.68263401	33.38
24.02605286	29.58
24.64292245	29.58
28.82976209	29.58
31.93005181	33.73
32.91842391	33.73
35.76234635	38.06
36.31706604	38.06

39.7150431	38.06
40.67657424	42.04
42.12350638	42.04
42.8434002	42.04
44.59	39.99
52.88	42.89
57.46	53.91
28.59	31.64
34.1	34.39
39.59	47.16
15.25	22.12
22.38	24.26
35.2	37.07
47.3033537	48.96
32.50580381	32.83
37.90490985	41.62
44.10388345	39.66
36.9050754	36.99
25.30699576	26.54
41.90424766	36.68
29.70626735	36.87
19.30798905	26.58
22.90739308	23.33
32.30583692	26.37
26.90673088	23.69
19.30798905	12.53
19.70792283	20.46
23.70726064	24.31
22.30749241	22.34
19.70792283	15.48
41.81	45.90
58.04	54.89
43.24	57.03
37.59	38.04
46.65	40.98
53.89	47.97
46.13	50.05
39.81	35.18

26.85	32.41
36.31	41.50
32.12	33.90
27.65	33.27
25.69	31.59
33.03	36.39
23.83	20.12
19.91	20.68
47.6	48.75
63.52	57.31
50.65	59.30
41.34	40.41
49.15	43.92
61.53	50.76
53.64	52.31
42.05	37.73
36.67	35.21
41.63	44.43
34.8	35.16
42.3	35.92
34.78	34.36
38.42	39.30
28.6	23.04
24.4	23.62
16.67408745	18.56
19.08407654	19.42
30.29733684	29.87
36.48917792	34.61
17.73729623	18.80
20.08714893	19.69
31.80401899	31.53
38.08091366	38.81
15.42997543	17.21
18.08353808	17.99
27.51842752	27.35
32.53071253	32.17
13.95577396	16.20
16.11793612	16.93

26.04422604	27.10
29.87714988	32.87
15.72481572	17.44
18.08353808	18.25
28.7960688	29.27
33.90663391	35.84
14.39465479	16.20
17.08939061	16.93
27.22693625	27.10
31.96262869	32.87
12.95510303	14.07
15.06037891	14.66
23.74888792	22.34
28.08480194	25.77
13.93592784	14.24
15.89423096	14.85
25.83911346	23.73
28.86736346	30.50
11.13628718	13.15
13.66187707	13.68
21.05146811	20.30
25.26478927	23.15
10.66221347	12.48
12.39728002	12.97
20.57691384	20.22
23.68422317	24.17
12.40136479	13.31
13.89927435	13.86
21.68388678	21.92
26.84607622	27.29
11.20086269	12.48
13.09100365	12.97
21.40176799	20.22
24.75357757	24.17
19.00752454	20.74
22.04656081	21.72
34.59229666	33.11
26.12922092	37.71

19.98563305	21.02
23.09298341	22.02
36.19115808	34.87
41.50767557	41.70
16.9375	19.21
19.63282967	20.11
30.98008242	30.45
37.2103022	35.42
15.9375	18.05
18.43282967	18.89
29.68035714	30.18
34.71057692	36.06
18.1375	19.47
20.63255495	20.39
32.58008242	32.49
39.31057692	38.89
16.70655199	18.05
19.51466629	18.89
30.97222706	30.18
35.7525599	36.06
14.83978931	15.59
16.98687872	16.28
26.55697493	25.02
32.04692985	29.22
15.75112086	15.78
17.8075247	16.49
27.33256875	26.52
33.65120781	33.75
13.46266875	14.51
28.76499645	15.14
15.41032044	22.79
24.15249252	26.64
12.54481036	13.72
14.24440116	14.30
23.61437592	22.63
27.22875185	27.49
13.80041575	14.70
16.12780923	15.34

24.9596674	24.52
30.90614337	30.59
12.69039095	13.72
15.39102456	14.30
24.11875839	22.63
27.66379635	27.49

It could be seen that there are some differences between the real value and the predicted value.

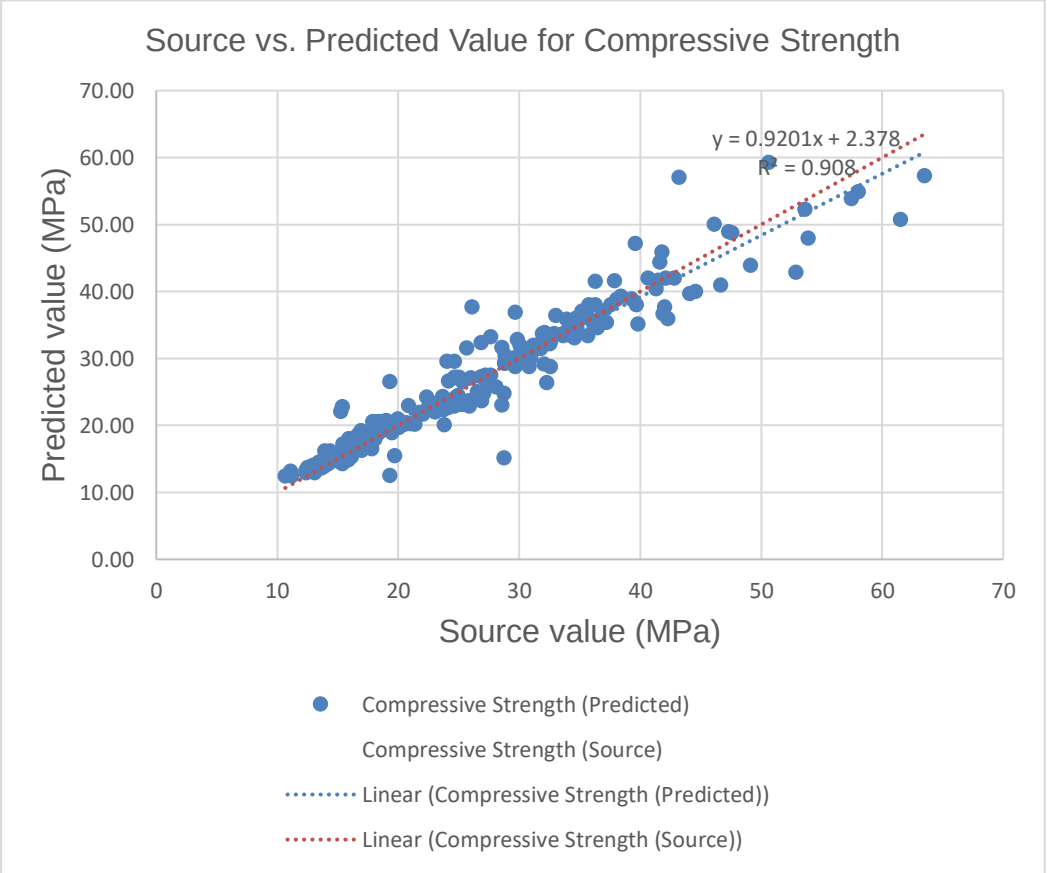


Figure 5.3.12 Source vs. Predicted Value for Compressive Strength

The chart would confirm the extent of similarity between the source value and the predicted value. The comparison between the y=x

trendline also highlights the difference between the real and predicted values. The graph also shows the areas where the outliers are.

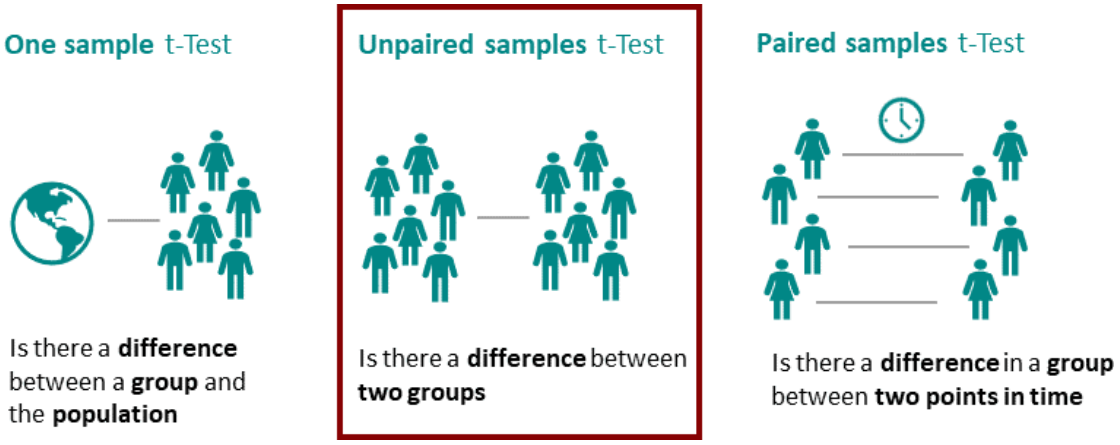


Figure 5.3.13 Different kinds of t-test (DATAtab Team, 2022)

From the figure above it can be seen that an unpaired samples t-test would be the t-test that would be most appropriate when looking at the difference between two groups. We are eager to see the difference between the real values and the values from the model to determine if the model is sufficiently similar.

Table 5.3-7 Comparison between real and predicted values when the neural network is applied to the original dataset.

	Compressive Strength (Source)	*Compressive Strength (Predicted)*
Mean	28.1145082	28.24733733
Variance	118.609677	110.5988537
Observations	189	189
Hypothesized Mean Difference	0	
df	376	

t Stat	-0.120617089	
P(T<=t) one-tail	0.45202938	
t Critical one-tail	1.648916269	
P(T<=t) two-tail	0.904058759	
t Critical two-tail	1.966293229	

From the table above, the P(T<=t) is greater than 0.05 for both one-tail and two-tail. This would indicate that the predictions are sufficiently similar with the real values. The predictions, however, are only sufficiently accurate for the 10-42 MPa range. This could be seen as the values above 42 MPa are scarce.

5.3.3.2 Tweaked neural network code

```
function [Y,Xf,Af] = DTNNet2coder(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 13-Jul-2022 22:56:12.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = 21xQ matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of
timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 6 7 8 10 12 13 14 16 17 18 21];
x1_step2.xoffset = [134.6;0;362.5;0;96.9;0.33;1565.35;0;0;0;0;0;0;0;3];
```

```
x1_step2.gain =
[0.00534188034188034;0.0020242914979757;0.00253936008125952;0.002
02429149797571;0.0137835975189524;9.09090909090909;0.002401969615
08437;0.0195121951219512;0.248138957816377;0.0192492781520693;0.00
579206487112656;20;2;1.66666666666667;0.0377358490566038];
x1_step2.ymin = -1;

% Layer 1
b1 = [2.543097735234663 7588;-9.1382131543750872993];
IW1_1 = [-0.29346197381831606865 4.7402130464559926182
2.631100712658445584 4.8094416349432238533 1.2915264196263442908
-0.72253292923563483541 -2.4005504819454901444
0.20435252178906523901 -0.18907576534553460768 -
0.76123515660668772398 0.85255204055838507138 -
0.005534632306831427 7199 0.050505046506485691549 -
0.34136818316556299946 -0.55490083327924466516;-
3.7798396072313593663 2.8869943041344634516
5.4929138791179177304 2.7776691995891127362
0.47194011553239623158 -3.565539346908419116
1.5485215482395500164 0.43480484276587494374 -
14.895104410095123981 3.4220597560976471208 -
1.3564644620896748606 0.49608514012807730653
0.018173699611249316543 -3.208119310204490926 -
2.5370685010539615334];

% Layer 2
b2 = -0.17127292492880508146;
LW2_1 = [-1.3291295220081387196 0.33387503439469362609];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0378373770662546;
y1_step1.xoffset = 10.6622134653275;

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
    X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
```

```
    Q = size(X{1},2); % samples/series
else
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

    % Input 1
    temp = removeconstantrows_apply(X{1,ts},x1_step1);
    Xp1 = mapminmax_apply(temp,x1_step2);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Remove Constants Input Processing Function
```

```
function y = removeconstantrows_apply(x,settings)
y = x(settings.keep,:);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

5.4 Needed variables for NDT and DT

The needed variables could be found using both PCA and linear regression as a basis for the values.

Table 5.4-1 Different variables deemed necessary by different analysis.

	PCA NDT	Linear Regression NDT	PCA DT	Linear Regression DT
Cement (kg/m^3)	1	2	1	
Coarse aggregates (kg/m^3)	1	2	1	2
Fine aggregates (kg/m^3)	1	2	1	2
Coarse RCA (kg/m^3)	1	2	1	2
Fine RCA (kg/m^3)	1	2		
Water content (kg/m^3)	1	2	1	
Water to binder ratio				2

Total Unit Weight (kg/m^3)	1	2	1	2
Granite Fines (kg/m^3)		2		
Fly ash content (kg/m^3)		2		
Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)		2		
Nano Silica (kg/m^3)				2
Filler (kg/m^3)	1	2	1	
Crumb Rubber (kg/m^3)	1	2	1	2
Metakaolinite Content (kg/m^3)		2		
polypropylene fibre (% by volume)				
dry curing				2
Superplasticizer (%)		2		
(Schmidt) Rebound number		2		
UPV (km/s)		2		
Age of concrete (days)				2

The rationale for creating the table is to find the most needed factors. This would allow a minimization of the required variables while keeping most of the accuracy of the model.

Table 5.4-2 Different variables deemed necessary by different analysis. The orange variables are ones that are deemed necessary only by PCA, yellow are ones that are deemed necessary only by linear regression and green is deemed

necessary by both.

	NDT	DT
Cement (kg/m^3)	3	1
Coarse aggregates (kg/m^3)	3	3
Fine aggregates (kg/m^3)	3	3
Coarse RCA (kg/m^3)	3	3
Fine RCA (kg/m^3)	3	0
Water content (kg/m^3)	3	1
Water to binder ratio	0	2
Total Unit Weight (kg/m^3)	3	3
Granite Fines (kg/m^3)	2	0
Fly ash content (kg/m^3)	2	0
Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)	2	0
Nano Silica (kg/m^3)	0	2
Filler (kg/m^3)	3	1
Crumb Rubber (kg/m^3)	3	3
Metakaolinite Content (kg/m^3)	2	0
polypropylene fibre (% by volume)	0	0
dry curing	0	2
Superplasticizer (%)	2	0

(Schmidt) Rebound number	2	0
UPV (km/s)	2	0
Age of concrete (days)	0	2

From the analysis shown, it could be seen that the important parameters for NDT are as follows: cement, fine aggregates, coarse aggregates, coarse RCA, fine RCA, water content, total unit weight, granite fines, fly ash content, ground granulated blast furnace slag, filler, crumb rubber, metakaolinite content superplasticizer %, rebound number, and UPV.

It could also be seen that the important parameters for DT are as follows: cement, fine aggregates, coarse aggregates, coarse RCA, water content, water-to-binder ratio, total unit weight, nano silica, filler, crumb rubber, dry curing, and age of concrete in days.

Table 5.4-3 Combined table for needed variables. The combined table uses the maximum between the two columns of the previous table.

	Combined
Cement (kg/m^3)	3
Coarse aggregates (kg/m^3)	3
Fine aggregates (kg/m^3)	3
Coarse RCA (kg/m^3)	3
Fine RCA (kg/m^3)	3

Water content (kg/m^3)	3
Water to binder ratio	2
Total Unit Weight (kg/m^3)	3
Granite Fines (kg/m^3)	2
Fly ash content (kg/m^3)	2
Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)	2
Nano Silica (kg/m^3)	2
Filler (kg/m^3)	3
Crumb Rubber (kg/m^3)	3
Metakaolinite Content (kg/m^3)	2
polypropylene fibre (% by volume)	0
dry curing	2
Superplasticizer (%)	2
(Schmidt) Rebound number	2
UPV (km/s)	2
Age of concrete (days)	2

We can also combine the two tables. However, we would use instead the previous table. This is because using the combined table only eliminates the need for polypropylene fibers.

5.5 Using important NDT Factors only

5.5.1 Linear Regression

Linear regression is used here since it is the most intuitive method by which a data analysis could be understood. Linear regression is of form $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$, which makes it very intuitive to understand and use.

Table 5.5-1 Result using linear regression.

	Estimate	SE	tStat	pValue
(Intercept)	-48.122	6.0766	-7.9192	8.03E-14
Cementkgm3	-0.15694	0.0285	-5.5004	9.42E-08
CoarseAggregateskgm3	-0.17751	0.0286	-6.2095	2.22E-09
FineAggregateskgm3	-0.18159	0.0286	-6.3423	1.06E-09
CoarseRCAkgm3	-0.17833	0.0286	-6.2291	2.00E-09
FineRCAkgm3	-0.17957	0.0286	-6.2724	1.57E-09
WaterContentkgm3	-0.10097	0.0313	-3.2248	0.00143
WaterToBinderRatio	0	0	NaN	NaN
TotalUnitWeightkgm3	0.18183	0.0286	6.3612	9.58E-10
GraniteFineskgm3	-0.18769	0.0293	-6.398	7.79E-10
FlyAshContentkgm3	-0.17754	0.0301	-5.8952	1.22E-08
GroundGranulatedBlast FurnaceSlagGGBSkgm3	-0.22157	0.0323	-6.8555	5.61E-11
NanoSilicakgm3	0	0	NaN	NaN
Fillerkgm3	0.15921	0.0255	6.2523	1.76E-09
CrumbRubberkgm3	-0.07011	0.0137	-5.1019	6.69E-07
MetakaoliniteContentkgm3	-0.22202	0.0313	-7.0821	1.46E-11
polypropyleneFibreByVolume	0	0	NaN	NaN
dryCuring	0	0	NaN	NaN
Superplasticizer	11.682	1.4925	7.8272	1.45E-13
SchmidtReboundNumber	0.81317	0.055	14.774	7.37E-36
UPVkms	6.1574	0.7858	7.8362	1.37E-13
AgeOfConcretedays	0	0	NaN	NaN

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed. The result from the linear regression shows the importance of each of the variables and coefficient that they would add to the model. The NaN would indicate factors that do not exist within the dataset.

Table 5.5-2 Model training results

RMSE (Validation)	2.7464
R-Squared (Validation)	0.95
MSE (Validation)	7.5425
MAE (Validation)	2.0293
Prediction speed	~3000 obs/sec
Training time	11.983 sec

Table 5.5-3 Model parameters

Model Type	
Preset	Linear
Terms	Linear
Robust option	Off

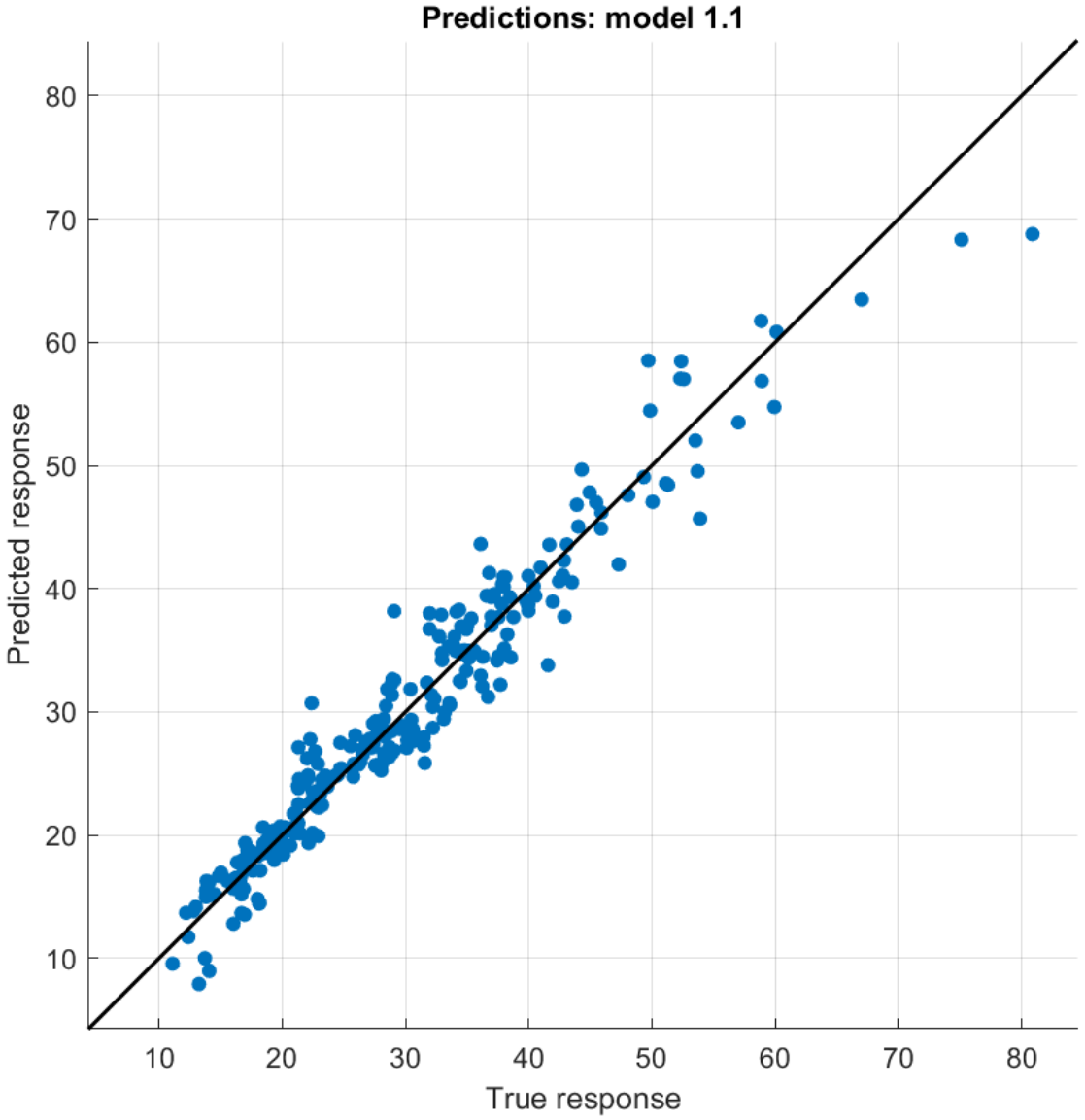


Figure 5.5.1 True vs Predicted for Linear Regression

The true vs predicted response graph shows the how much the

responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

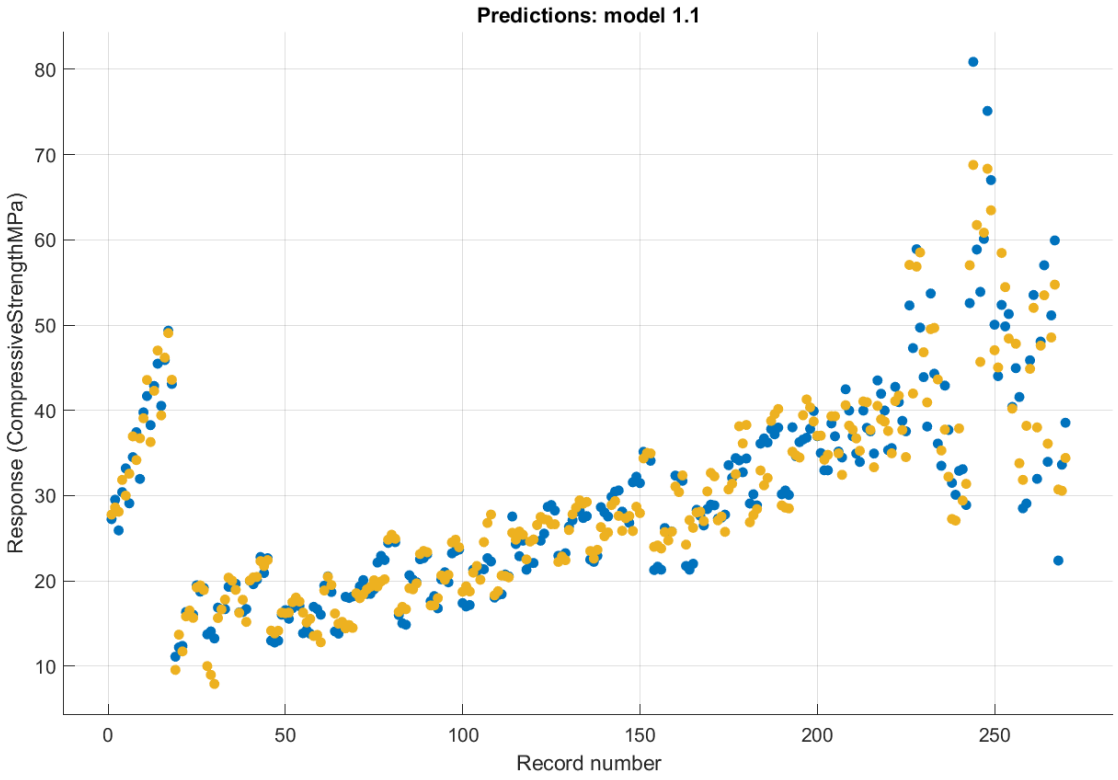


Figure 5.5.2 Response Plot for Linear Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.5.2 Stepwise Quadratic Regression with Interactions

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.5-4 Result by Stepwise Quadratic Regression with Interactions

	Estimate	SE	tStat	pValue
(Intercept)	-98.848	8.0751	-12.241	2.62E-27
Cementkgm3	-0.1286	0.02556	-5.0299	9.38E-07
CoarseAggregateskgm3	-0.0805	0.02548	-3.1608	0.00177
FineAggregateskgm3	-0.1638	0.02547	-6.4298	6.44E-10
CoarseRCAkgm3	-0.1826	0.0259	-7.0492	1.75E-11
FineRCAkgm3	-0.1664	0.0255	-6.5257	3.74E-10
WaterContentkgm3	0.17339	0.03785	4.5815	7.29E-06
TotalUnitWeightkgm3	0.1649	0.02542	6.4883	4.62E-10
GraniteFineskgm3	-0.1627	0.02605	-6.2456	1.80E-09
FlyAshContentkgm3	-0.1533	0.02693	-5.6904	3.54E-08
GroundGranulatedBlast FurnaceSlagGGBSkgm3	-0.2113	0.03585	-5.8937	1.22E-08
Fillerkgm3	0.10468	0.01968	5.3198	2.31E-07
CrumbRubberkgm3	-0.0616	0.01244	-4.9505	1.36E-06
MetakaoliniteContentkgm3	-0.1661	0.02688	-6.1784	2.61E-09
SchmidtReboundNumber	-0.2958	0.17524	-1.688	0.09266
UPVkms	7.7877	0.75199	10.356	3.81E-21
CoarseAggregateskgm3: WaterContentkgm3	-0.0003	3.25E-05	-10.774	1.76E-22
CoarseRCAkgm3: FineRCAkgm3	1.12E-05	4.42E-06	2.5469	0.01147
GroundGranulatedBlast FurnaceSlagGGBSkgm3: SchmidtReboundNumber	0.00125	0.00053	2.3832	0.01791
SchmidtReboundNumber^2	0.0159	0.00262	6.0785	4.51E-09

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed.

The result from the table shows the different coefficients and the result that they add to the model. A feature labeled as $A{:}B$ would add an interaction term $\beta_{AB}x_Ax_B$ to the standard linear equation. In other

Table 5.5-5 Model training results

RMSE (Validation)	2.5959
R-Squared (Validation)	0.95
MSE (Validation)	6.7388
MAE (Validation)	1.8251
Prediction speed	~9000 obs/sec
Training time	162.11 sec

Table 5.5-6 Model parameters

Model Type	
Preset	Stepwise Linear
Initial terms	Linear
Upper bound on terms	Quadratic
Maximum number of steps	1000

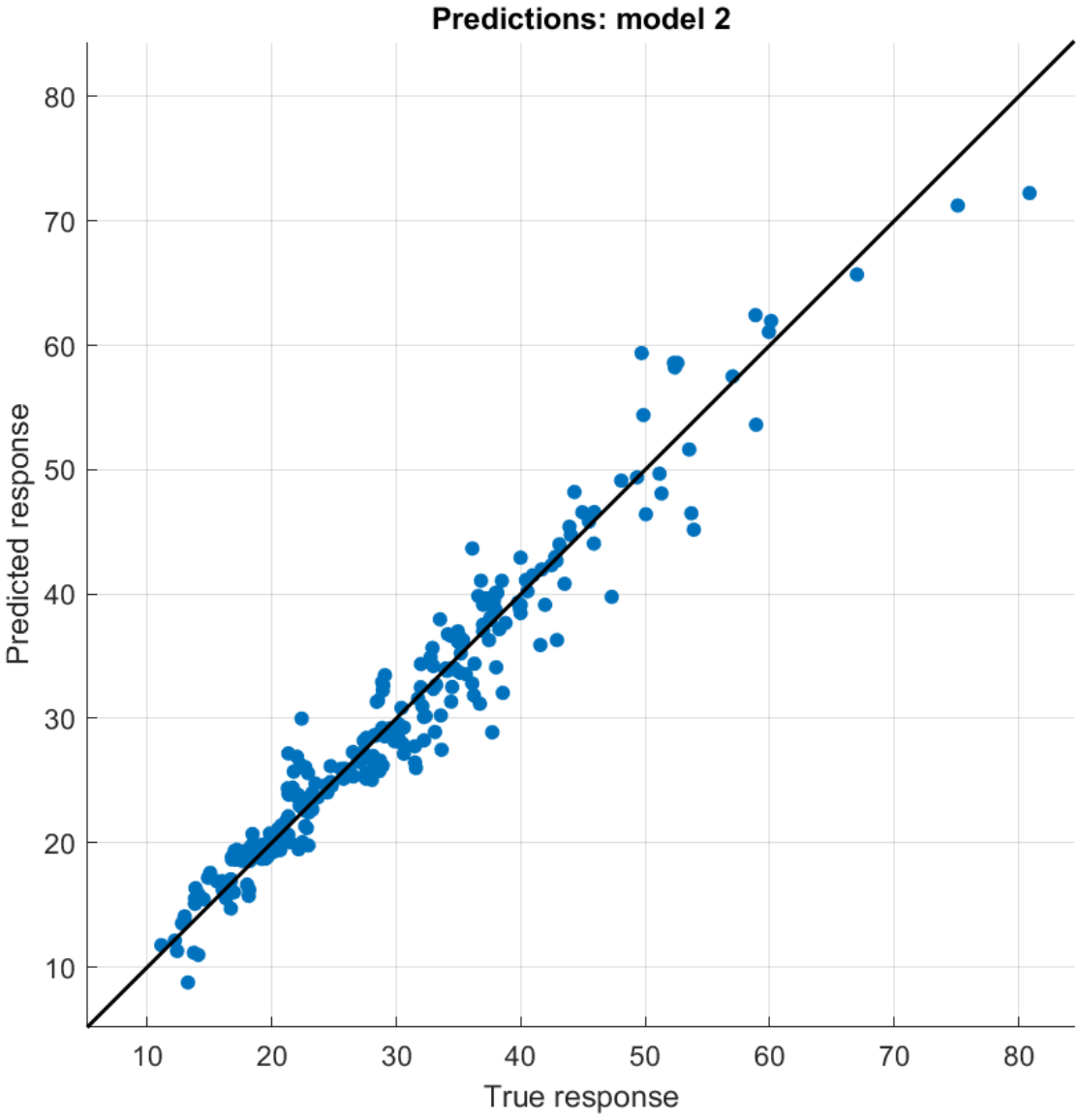


Figure 5.5.3 Predicted vs Actual for Stepwise Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

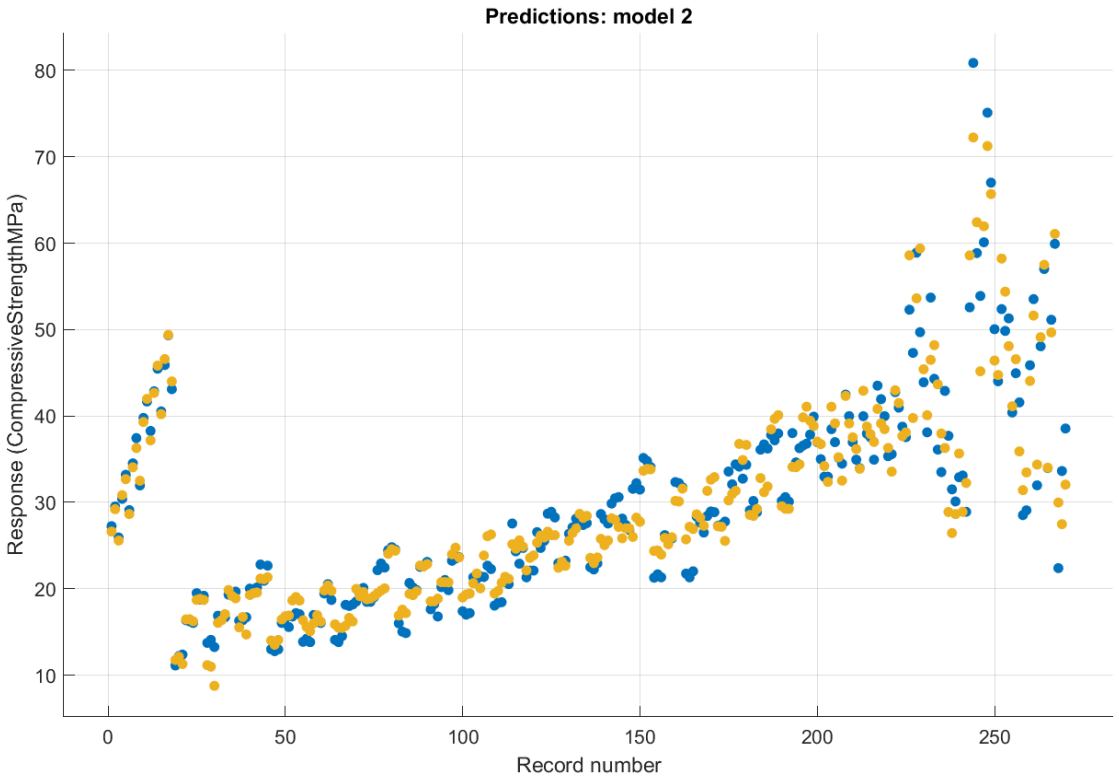


Figure 5.5.4 Response Plot for Stepwise Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.5.3 Tweaked neural network for important NDT factors

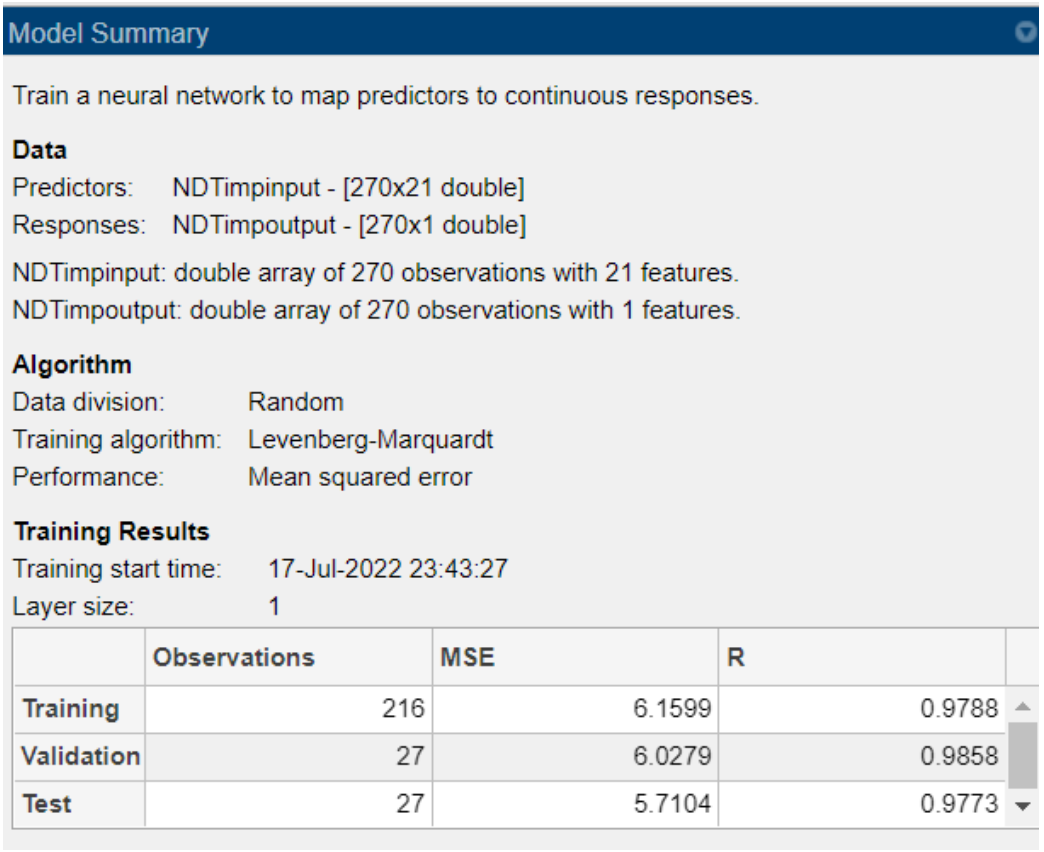


Figure 5.5.5 Model Summary.

The Figure above shows the summary of the model. The R value shown indicates that the model created is a good match to the data given. Moreover, the closeness of the mean square error between training, validation and test means that no overfitting has occurred. The test-train ratio of 80:20 is also implemented. This result is chosen since the mean squared error is lower than the value obtained using other methods, such as stepwise regression.

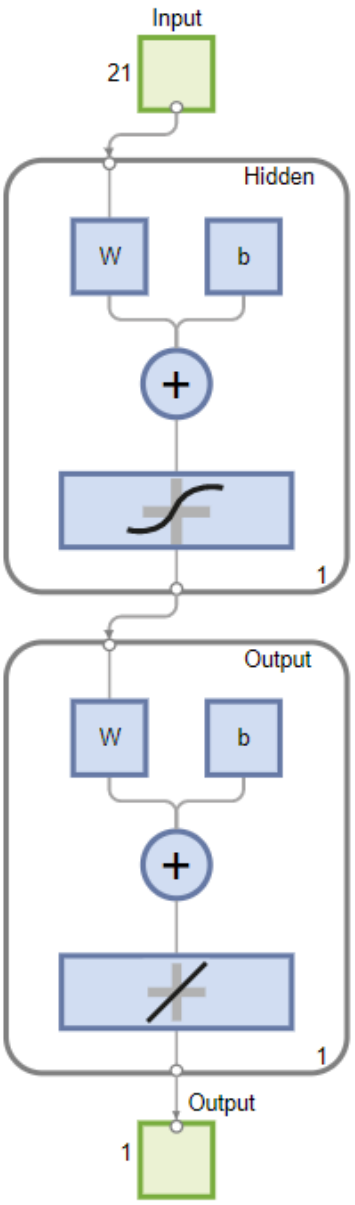


Figure 5.5.6 Diagram of the neural network.

The Figure above shows that a sigmoid activation is used. It also shows that there are 21 features as input and 1 as output. It also shows that the hidden layer has a size of 1.

Training Results

Training finished: Met validation criterion

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	30	1000
Elapsed Time	-	00:00:00	-
Performance	629	5.39	0
Gradient	1.88e+03	5.76	1e-07
Mu	0.001	0.1	1e+10
Validation Checks	0	6	6

Figure 5.5.7 Training progress with elapsed time and different stopping criteria

The Figure above shows that the machine learning run is successful. Namely, the mean squared error has decreased. This is shown under performance. The training was finished by meeting the validation criteria, which is that for 6 consecutive iterations, the validation error increases.

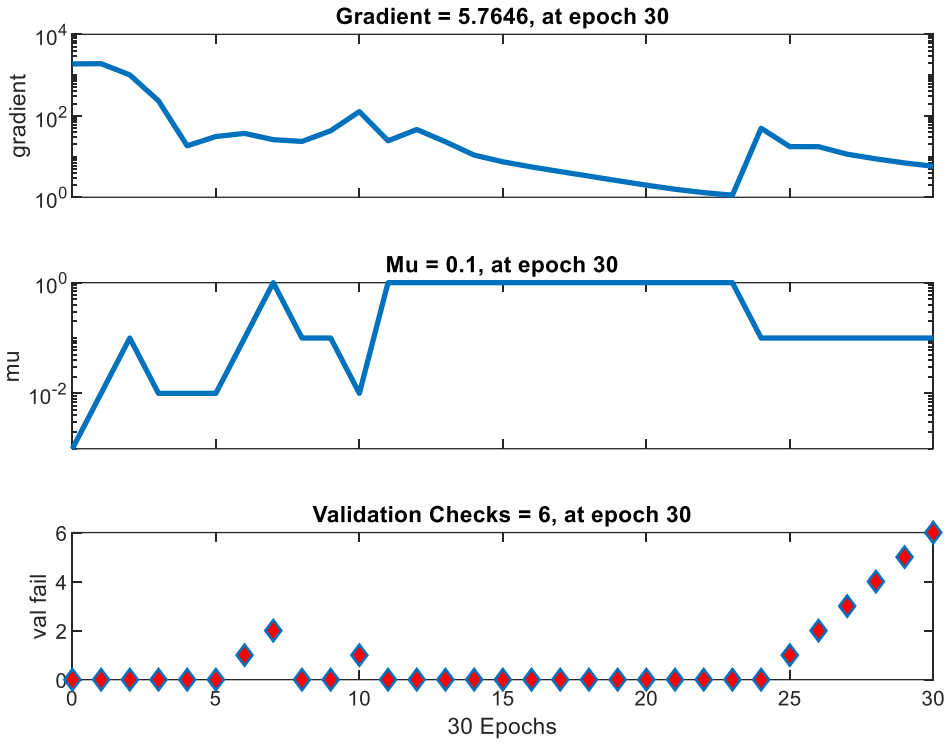


Figure 5.5.8 Different charts showing the various training parameters.

The gradient chart shows that the steps needed to reach the goal gets smaller, which is the expected outcome.

The mu chart measures How close to the newton's method the analysis would be. A high mu would make the algorithm be equivalent to gradient descent with small steps, while a small mu would make the algorithm be closer to newton's method. It is beneficial to get to Newton's method as quickly as possible since it is faster and is more accurate near an error minimum. Thus, mu is decreased after each successful step (reduction in performance function) and is increased

only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

The validation checks show the accumulated amount of validation checks failed in a row. The chart looks as expected since the six failures of each epoch to increase the performance on the validation test caused the test to be finished.

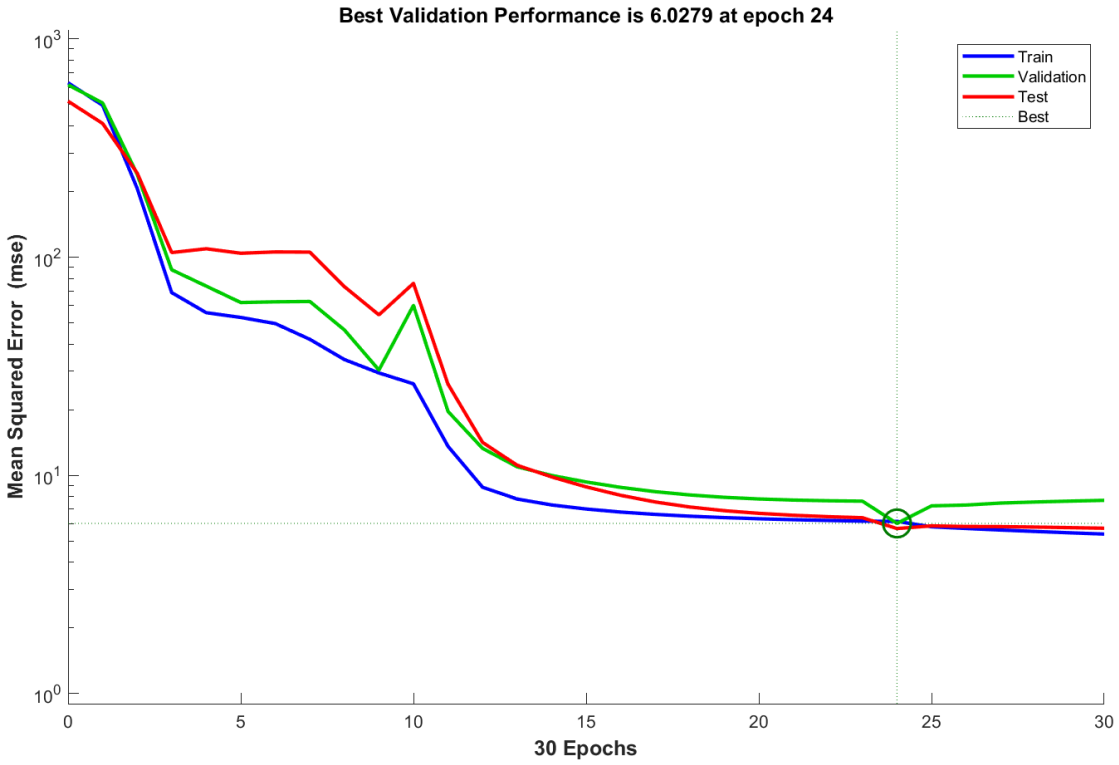


Figure 5.5.9 Performance (Mean squared error) for each of the epochs or train, validation, and test.

The Figure above shows that the neural network is improving. I also show that the best version of the neural network was found on epoch 24.

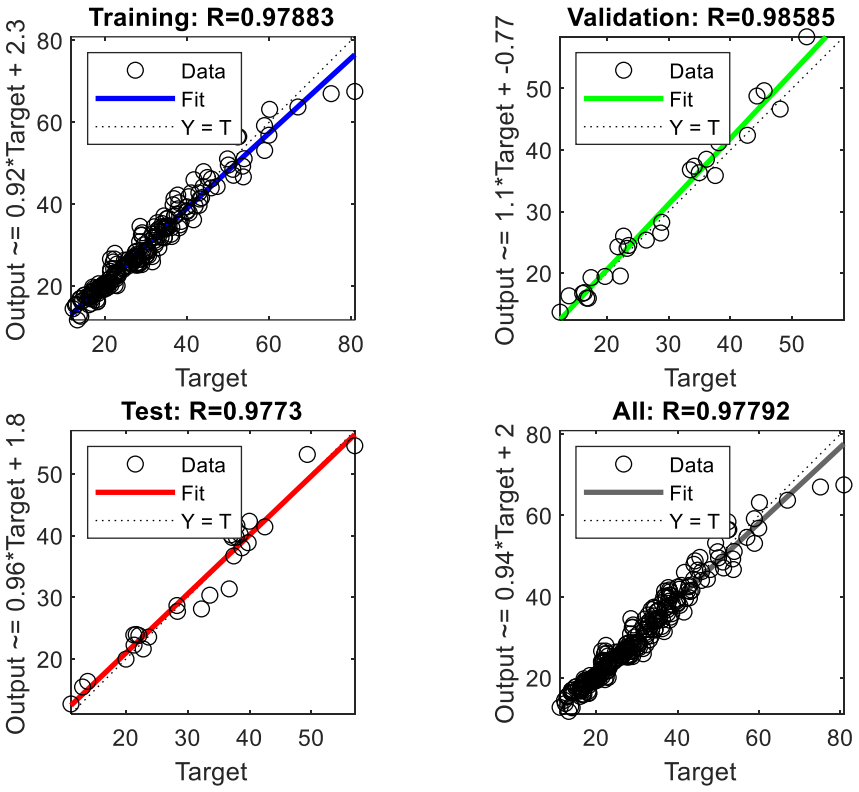


Figure 5.5.10 Charts showing the correlation between the target and the output.

The Figure above shows that the neural network is predicting well. Moreover, it demonstrates that there is much alignment between the output of the neural network and the target value.

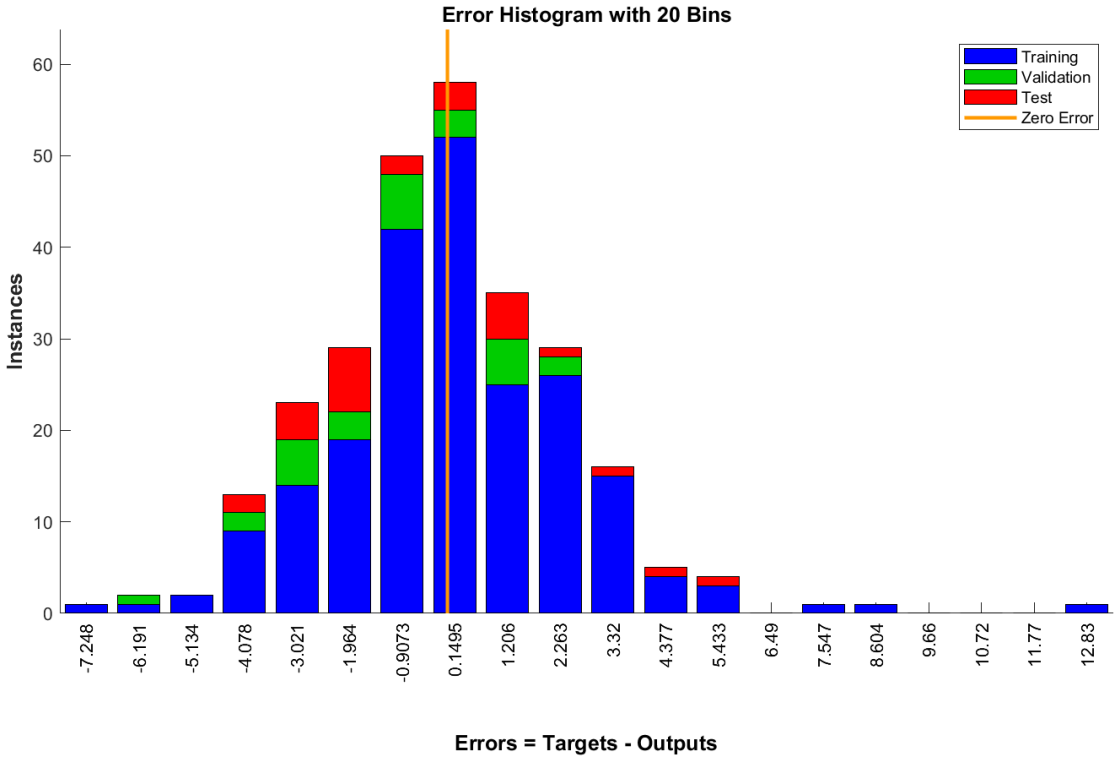


Figure 5.5.11 Error histogram of the neural network.

The error histogram mostly follows the curve expected from the neural network, namely that except for outliers, the errors follow the normal distribution. Nevertheless, the outliers show the blind spots of the model.

5.5.3.1 Comparison between predicted values vs real values

The comparison of predicted values vs real values is used to see to what extent the predictions will align with the real data. The

comparison is as follows:

Table 5.5-7 Comparison between real and predicted values when the neural network is applied to the original dataset.

Compressive Strength (Source)	Compressive Strength (Predicted)
27.25	27.19
29.52	30.04
25.93	25.80
30.41	30.81
33.2	32.50
29.1	28.22
34.52	34.27
37.44	36.70
31.96	32.01
39.77	38.85
41.68	45.95
38.27	34.92
42.86	42.73
45.47	49.64
40.53	37.82
45.9	46.12
49.34	53.16
43.1	41.22
11.117673	12.70
12.207564	14.43
12.382182	13.64
16.35327	16.86
16.229664	17.23
16.044255	16.70
19.489527	19.36
18.747891	19.36
19.183455	19.19
13.734	12.85
14.082255	12.58
13.254291	11.69
16.8732	16.82

16.655418	17.36
16.698582	18.13
19.314909	20.09
19.270764	19.98
19.663164	19.45
16.311087	16.81
16.35327	17.73
16.698582	15.93
20.0124	19.97
19.62	20.09
20.142873	20.03
22.802364	21.62
20.927673	21.56
22.671891	21.75
12.992364	15.45
12.774582	15.30
12.98844	15.50
16.044255	17.33
16.568109	17.33
15.565527	17.38
16.792758	18.61
17.178291	18.84
17.047818	18.61
13.864473	16.88
14.213709	16.20
13.821309	16.30
16.960509	15.89
16.698582	15.74
16.044255	15.39
19.445382	19.33
20.535273	20.40
18.704727	19.80
14.082255	16.94
13.821309	16.36
14.5188	16.41
18.137709	16.11
18.006255	16.63
18.180873	16.26

18.530109	19.64
19.358073	19.00
20.099709	19.29
18.485964	19.10
18.485964	19.22
19.009818	19.69
22.149018	19.51
22.933818	20.05
22.454109	20.17
24.459273	24.04
24.808509	24.85
24.546582	24.37
16.001091	17.32
15.03873	17.76
14.867055	17.71
20.666727	19.64
20.142873	19.52
19.837782	20.06
22.541418	22.93
22.671891	22.99
23.107455	22.86
17.61876	18.12
18.225018	18.12
16.785891	18.62
20.187018	20.62
21.014982	20.63
19.837782	20.62
23.238909	24.01
23.499855	24.48
23.674473	23.54
17.396073	19.26
17.003673	19.73
17.178291	19.32
21.320073	20.93
21.145455	21.74
21.451527	20.26
21.364218	24.15
22.671891	26.00

22.279491	26.57
18.0504	18.89
18.355491	19.23
18.4428	20.54
20.753055	20.78
20.535273	20.60
27.555309	25.07
24.3288	24.45
22.900464	25.34
24.7212	24.79
21.320073	22.25
22.10193	23.81
22.104873	24.21
26.552727	25.51
24.7212	26.28
25.549164	26.35
28.688364	26.50
28.907127	26.50
28.2528	26.50
22.9554	22.42
22.933818	22.68
23.2497	22.62
26.35947	25.36
27.118764	26.55
28.122327	27.12
28.2528	28.66
27.380691	28.22
27.598473	28.44
22.497273	23.35
22.236327	22.57
22.933818	23.35
28.6452	25.65
28.035018	25.10
27.555309	25.30
29.865564	28.60
30.476727	28.45
30.6072	27.43
28.122327	25.40

27.380691	26.45
26.813673	26.80
31.566618	25.89
32.219964	28.11
31.479309	27.16
35.141382	34.16
34.793127	33.91
34.094655	33.83
21.276909	23.90
21.669309	23.97
21.320073	23.57
26.203491	25.47
25.767927	24.92
25.811091	25.54
32.351418	30.67
32.219964	29.99
31.740255	31.68
21.756618	24.27
21.320073	26.56
22.017564	25.85
28.340109	27.71
27.642618	27.64
26.508582	26.56
28.427418	30.80
28.950291	32.44
28.862982	32.36
27.293382	26.85
27.423855	27.06
27.773091	25.65
33.571782	30.34
32.089491	31.10
34.400727	31.73
34.1388	37.37
32.743818	35.44
34.356582	37.11
29.080764	27.01
30.159864	27.59
28.862982	28.25

36.1008	32.62
36.710982	31.36
36.231273	32.06
37.800873	38.84
37.190691	39.70
37.975491	40.31
30.170655	28.81
30.6072	28.51
30.084327	28.51
38.018655	34.19
34.618509	33.94
36.275418	34.27
36.580509	39.83
36.798291	41.32
37.845018	39.74
39.92277992	39.33
36.96911197	37.16
35	36.37
32.97297297	33.74
32.97297297	33.30
38.47490347	40.22
36.96911197	40.12
35.17374517	34.71
34.47876448	31.93
42.47104247	41.42
39.98069498	38.39
36.96911197	37.03
34.94208494	36.31
33.95752896	34.49
39.98069498	42.32
37.95366795	41.59
37.54826255	37.51
34.94208494	34.59
43.51351351	41.53
41.94980695	39.49
39.98069498	38.17
35.34749035	36.57
35.57915058	34.60

42.76061776	42.39
40.96525097	42.73
38.76447876	38.03
37.54826255	35.85
52.30252596	56.40
47.3033537	44.29
58.90143334	53.10
49.70295638	57.48
43.90391656	44.24
38.10487674	41.18
53.70229419	46.64
44.30385034	48.78
36.10520784	38.50
33.50563827	36.78
42.90408211	39.68
37.70494296	42.21
31.50596936	32.66
30.10620113	27.53
32.90573759	33.76
33.10570448	29.34
28.90639979	25.20
52.58	56.48
80.87	67.51
58.86	59.18
53.9	51.09
60.11	63.14
75.11	66.98
67.01	63.72
50.05	49.53
44.02	47.92
52.37	58.40
49.85	51.04
51.3	47.03
40.41	41.79
44.95	46.49
41.57	36.16
28.52	34.55
29.08	32.99

45.87	43.96
53.53	49.25
31.97	34.45
48.07	46.65
57.02	54.57
33.97	35.23
51.14	48.49
59.93	56.83
22.39	27.97
33.63	31.84
38.55	35.75

It could be seen that there are some differences between the real value and the predicted value.

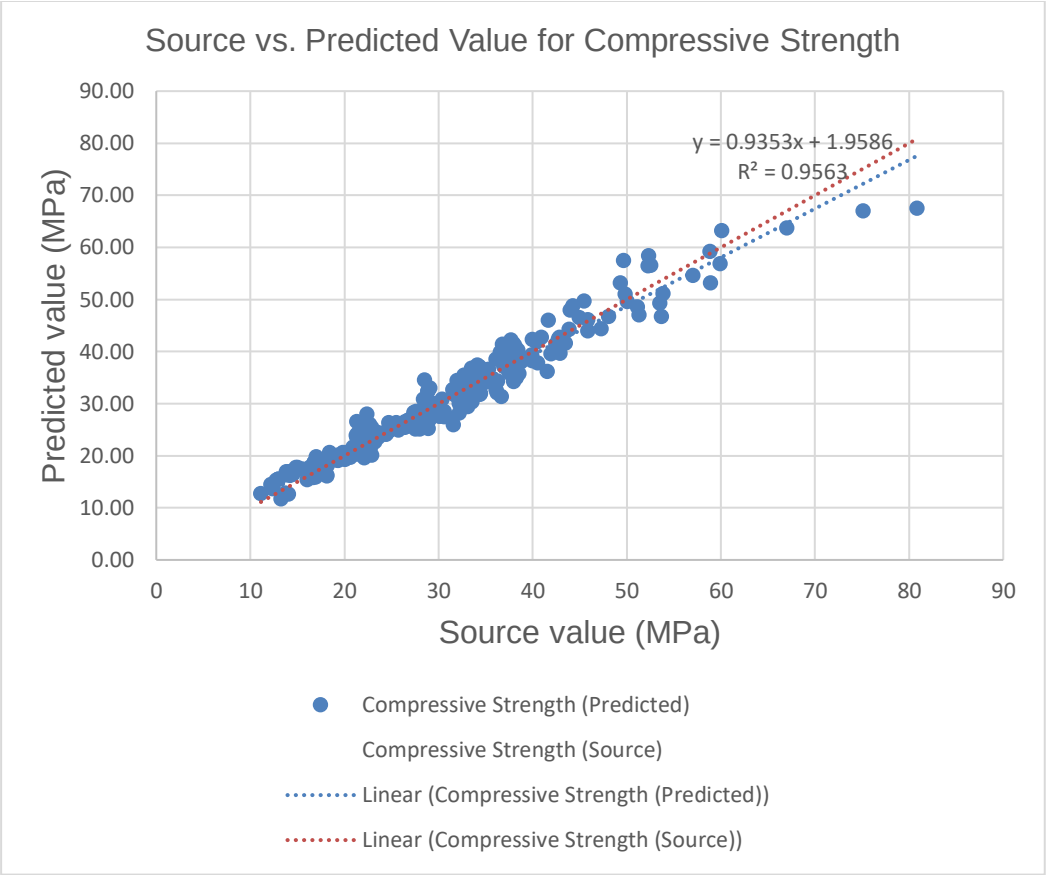


Figure 5.5.12 Source vs. Predicted Value for Compressive Strength

The chart would confirm the extent of similarity between the source value and the predicted value. The comparison between the y=x trendline also highlights the difference between the real and predicted values. The graph also shows the areas where the outliers are.

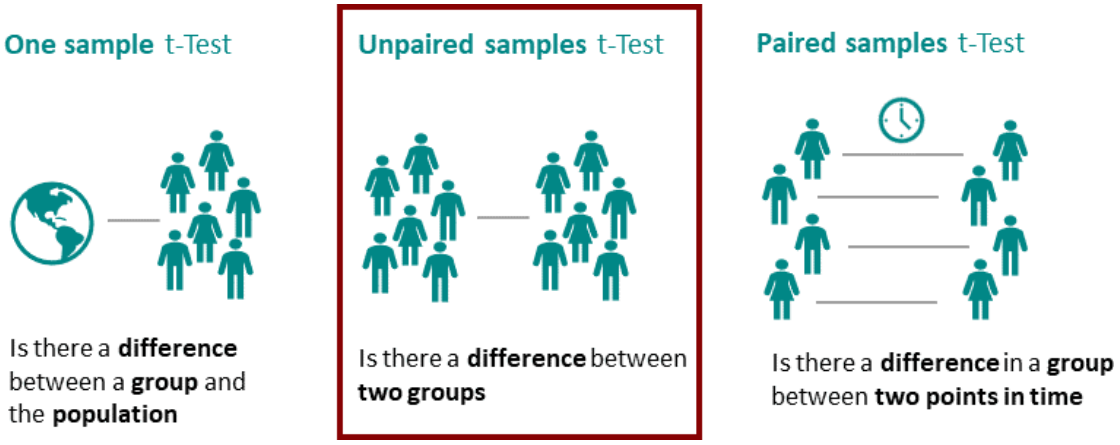


Figure 5.5.13 Different kinds of t-test (DATAtab Team, 2022)

From the figure above it can be seen that an unpaired samples t-test would be the t-test that would be most appropriate when looking at the difference between two groups. We are eager to see the difference between the real values and the values from the model to determine if the model is sufficiently similar.

Table 5.5-8 Comparison between real and predicted values when the neural network is applied to the original dataset.

	Compressive Strength (Source)	*Compressive Strength (Predicted)*
Mean	29.41937114	29.47589941
Variance	138.6808975	126.8699962
Observations	270	270
Hypothesized Mean Difference	0	
df	537	
t Stat	-0.056999846	
P(T<=t) one-tail	0.47728326	
t Critical one-tail	1.647696117	
P(T<=t) two-tail	0.95456652	

t Critical two-tail	1.964391426	

From the table above, the P(T<=t) is greater than 0.05 for both one-tail and two-tail. This would indicate that the predictions are sufficiently similar with the real values. The predictions, however, are only sufficiently accurate for the 10-42 MPa range. This could be seen as the values above 42 MPa are scarce.

5.5.3.2 Tweaked neural network code

```
function [Y,Xf,Af] = NDTNNetImp3(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 17-Jul-2022 23:44:26.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = 21xQ matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of
timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 5 6 8 9 10 11 13 14 15 18 19 20];
x1_step2.xoffset = [0;0;0;0;0;35;1285.5;0;0;0;0;0;0;0;14;2.93890080756283];
x1_step2.gain =
[0.00389105058365759;0.0015503875968992 2;0.0017389792191983 3;0.003
06748466257669;0.002439024390243 9;0.0082644628099173 6;0.001778568
25255669;0.0060716454159077 1;0.004;0.009779951100244 5;0.0192492781
520693;0.0057920648711265 6;0.004;0.571428571428571;0.0526868947757
209;0.869905920796697];
```

```
x1_step2.ymin = -1;

% Layer 1
b1 = -0.70923997426089013807;
IW1_1 = [0.021014363643190939l9 -0.32680399700141615771 -
0.35375752065656462797 -0.17799997068152467738 -
0.23245902704647211645 0.15110307686759430479
0.3588828422217383296 -0.11807944164896123918 -
0.008405623l002064898949 -0.097885869070403835 89
0.20962362381938187683 0.028691738122860604987 -
0.21873183093228723561 0.36284490099979882505
0.28180062653067688982 0.19039559170014155876];

% Layer 2
b2 = 0.20107515242795612198;
LW2_1 = 1.594985355110133618;

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0286728785406686;
y1_step1.xoffset = 11.117673;

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
    X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},2); % samples/series
else
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

    % Input 1
```

```
    temp = removeconstantrows_apply(X{1,ts},x1_step1);
    Xp1 = mapminmax_apply(temp,x1_step2);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Remove Constants Input Processing Function
function y = removeconstantrows_apply(x,settings)
y = x(settings.keep,:);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
```

```
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

5.6 Using important DT Factors only

5.6.1 Linear Regression

Linear regression is used here since it is the most intuitive method by which a data analysis could be understood. Linear regression is of form $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$, which makes it very intuitive to understand and use.

Table 5.6-1 Result using linear regression.

	Estimate	SE	tStat	pValue
(Intercept)	-31.703	19.21	-1.6504	1.01E-01
Cementkgm3	0.1306	0.0143	9.1333	2.15E-16
CoarseAggregateskgm3	-0.27654	0.0417	-6.6382	4.26E-10
FineAggregateskgm3	-0.16893	0.0439	-3.8441	1.72E-04
CoarseRCAkgm3	-0.27991	0.0416	-6.7308	2.58E-10
FineRCAkgm3	0	0	NaN	NaN
WaterContentkgm3	-0.74888	0.1194	-6.2725	2.9E-09
WaterToBinderRatio	205.89	36.552	5.6328	7.4E-08
TotalUnitWeightkgm3	0.1892	0.0402	4.7097	5.19E-06
GraniteFineskgm3	0	0	NaN	NaN
FlyAshContentkgm3	0	0	NaN	NaN
GroundGranulatedBlast FurnaceSlagGGBSkgm3	0	0	NaN	NaN
NanoSilicakgm3	-0.55373	0.2124	-2.6068	0.00997
Fillerkgm3	0.1821	0.0661	2.7532	6.55E-03
CrumbRubberkgm3	-0.12064	0.0232	-5.1994	5.79E-07
MetakaoliniteContentkgm3	0	0	NaN	NaN
polypropyleneFibreByVolume	0	0	NaN	NaN
dryCuring	-2.5545	0.8811	-2.8992	0.00424
Superplasticizer	0	0	NaN	NaN
SchmidtReboundNumber	0	0	NaN	NaN

UPVkms	0	0	NaN	NaN
AgeOfConcretedays	0.33433	0.0206	16.237	3.5E-36

The estimate shows what the coefficient that would be attached to the factor would be. The standard error shows the variability of a coefficient. In order words, it shows how far apart the value that would have been predicted by regression from the other values. tStat is the estimate over the standard error. The pValue is the probability of the coefficient being insignificant, with 0.05 being the p value that is the threshold whether the value would be removed. The result from the linear regression shows the importance of each of the variables and coefficient that they would add to the model. The NaN would indicate factors that do not exist within the dataset.

Table 5.6-2 Model training results

RMSE (Validation)	4.7073
R-Squared (Validation)	0.81
MSE (Validation)	22.159
MAE (Validation)	3.3749
Prediction speed	~2300 obs/sec
Training time	10.679 sec

Table 5.6-3 Model parameters

Model Type	
Preset	Linear
Terms	Linear
Robust option	Off

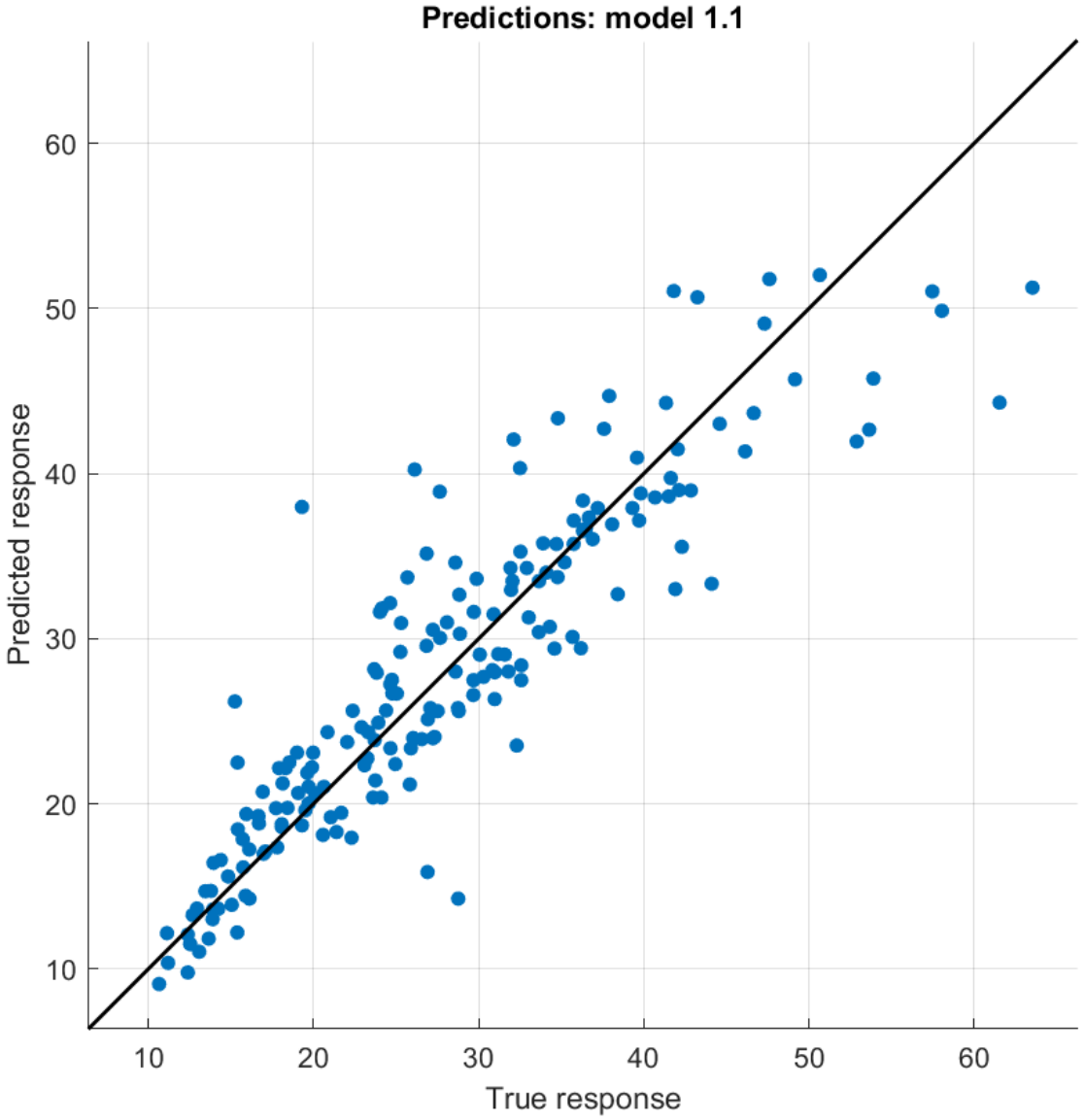


Figure 5.6.1 True vs Predicted for Linear Regression

The true vs predicted response graph shows the how much the

responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers and that most of the reliable data is between 10 to 45 MPa compressive strength.

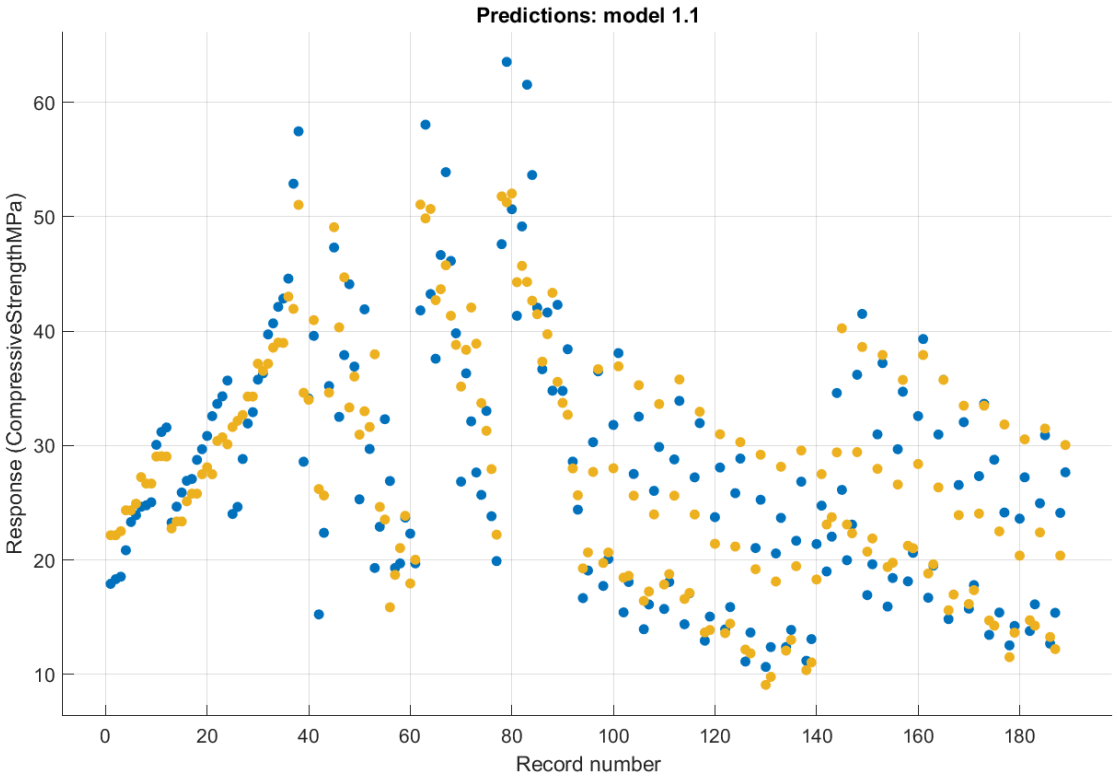


Figure 5.6.2 Response Plot for Linear Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.6.2 Matern 5/2 Gaussian Process Regression

This part has been added to give another method by which the neural network method should be able to beat.

Table 5.6-4 Model training results

RMSE (Validation)	3.8345
R-Squared (Validation)	0.88
MSE (Validation)	14.703
MAE (Validation)	2.5386
Prediction speed	~6500 obs/sec
Training time	1.1544 sec

Table 5.6-5 Model parameters

Model Type	
Preset	Matern 5/2 GPR
Basis function	Constant
Kernel function	Matern 5/2
Use isotropic kernel	true
Kernel scale	Automatic
Signal standard deviation	Automatic
Sigma	Automatic
Standardize	true
Optimize numeric parameters	true

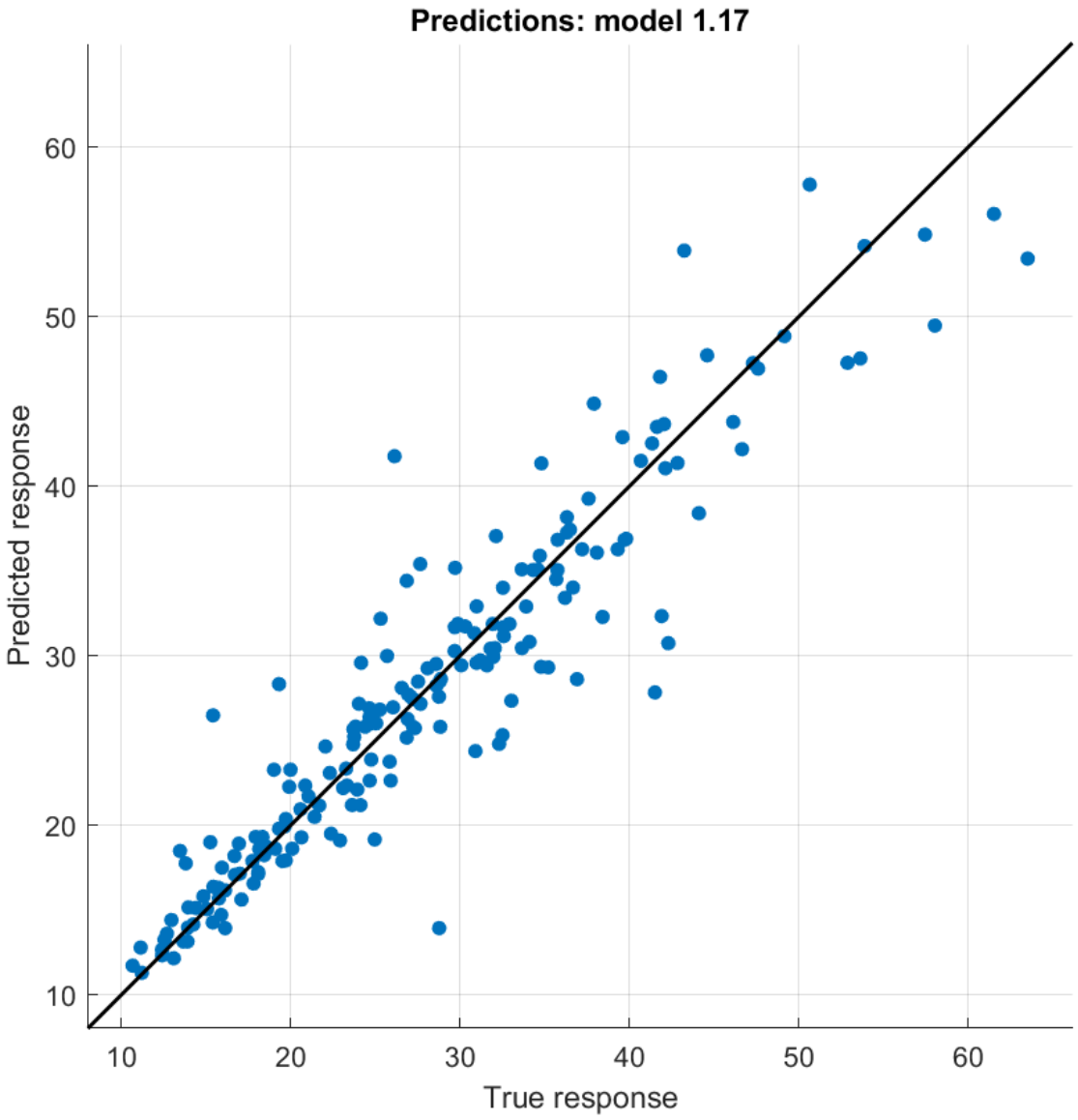


Figure 5.6.3 Predicted vs Actual for Matern 5/2 Gaussian Process Regression

The true vs predicted response graph shows the how much the responses would align. In this case, it shows to what extent the model could successfully predict. The graph shows that most of the observations are close. However, it also shows that there are outliers

and that most of the reliable data is between 10 to 45 MPa compressive strength.

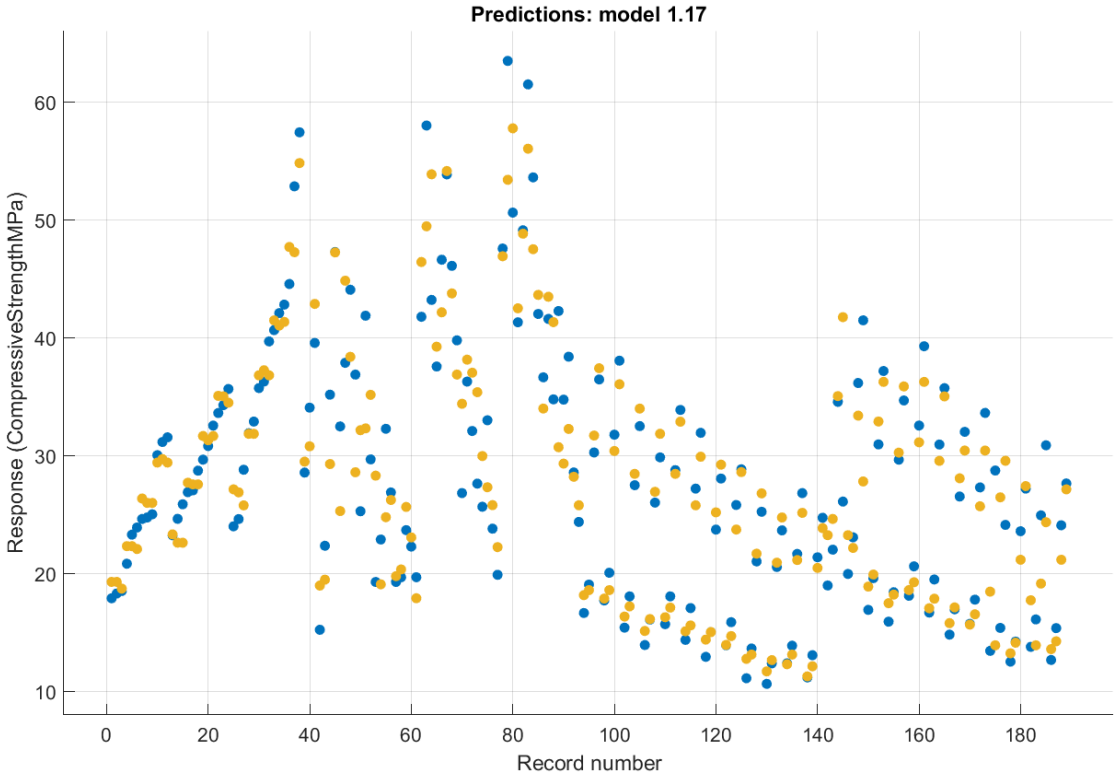


Figure 5.6.4 Response Plot for Matern 5/2 Gaussian Process Regression

The response plot shows how close the prediction would be when compared to the true values. In this case, it showed that the results to an extent match up to the true values.

5.6.3 Tweaked neural network for important destructive testing factors

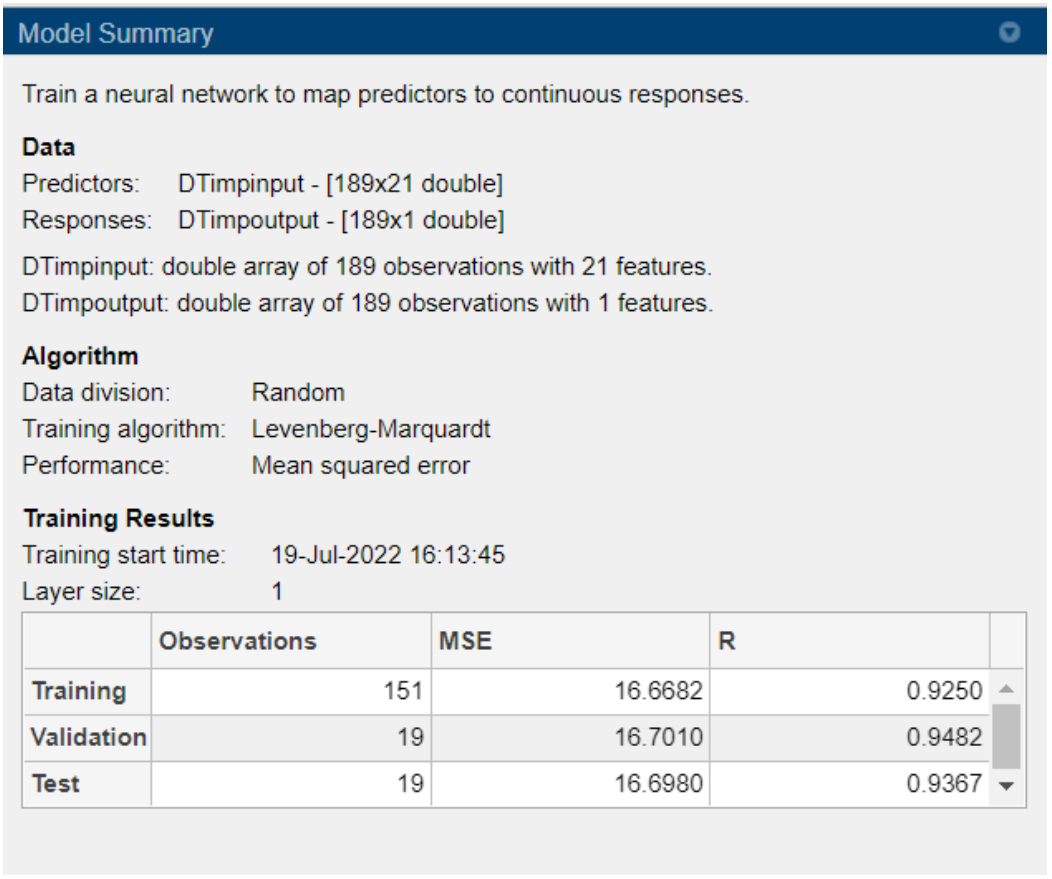


Figure 5.6.5 Model Summary.

The Figure above shows the summary of the model. The R value shown indicates that the model created is a good match to the data given. Moreover, the closeness of the mean square error between training, validation and test means that no overfitting has occurred. The test-train ratio of 80:20 is also implemented. This result is chosen since the mean squared error is lower than the value obtained using other methods, such as stepwise regression.

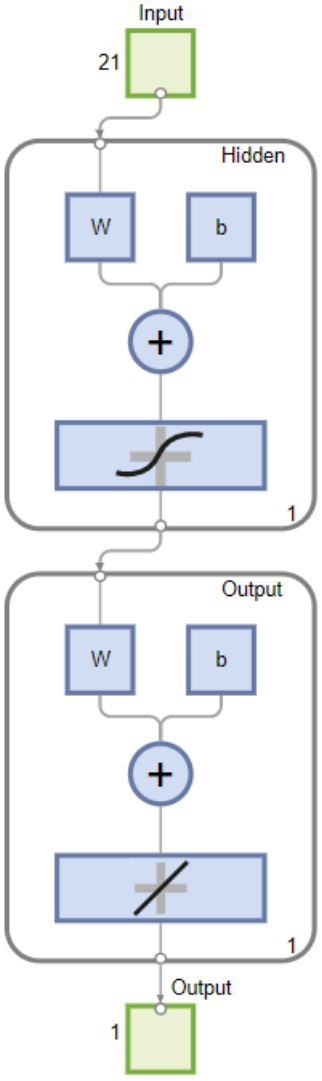


Figure 5.6.6 Diagram of the neural network.

The Figure above shows that a sigmoid activation is used. It also shows that there are 21 features as input and 1 as output. It also shows that the hidden layer has a size of 1.

Training Results

Training finished: Met validation criterion

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	88	1000
Elapsed Time	-	00:00:00	-
Performance	333	16.7	0
Gradient	886	2.28	1e-07
Mu	0.001	0.001	1e+10
Validation Checks	0	6	6

Figure 5.6.7 Training progress with elapsed time and different stopping criteria

The Figure above shows that the machine learning run is successful. Namely, the mean squared error has decreased. This is shown under performance. The training was finished by meeting the validation criteria, which is that for 6 consecutive iterations, the validation error increases.

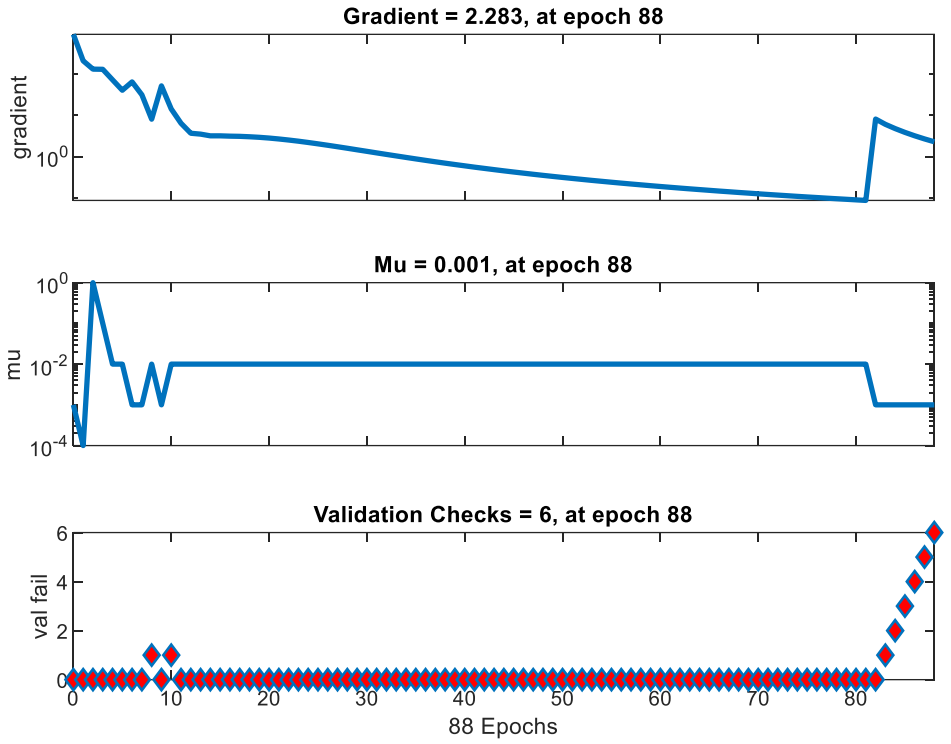


Figure 5.6.8 Different charts showing the various training parameters.

The gradient chart shows that the steps needed to reach the goal gets smaller, which is the expected outcome.

The mu chart measures How close to the newton's method the analysis would be. A high mu would make the algorithm be equivalent to gradient descent with small steps, while a small mu would make the algorithm be closer to newton's method. It is beneficial to get to Newton's method as quickly as possible since it is faster and is more accurate near an error minimum. Thus, mu is decreased after each successful step (reduction in performance function) and is increased

only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

The validation checks show the accumulated amount of validation checks failed in a row. The chart looks as expected since the six failures of each epoch to increase the performance on the validation test caused the test to be finished.

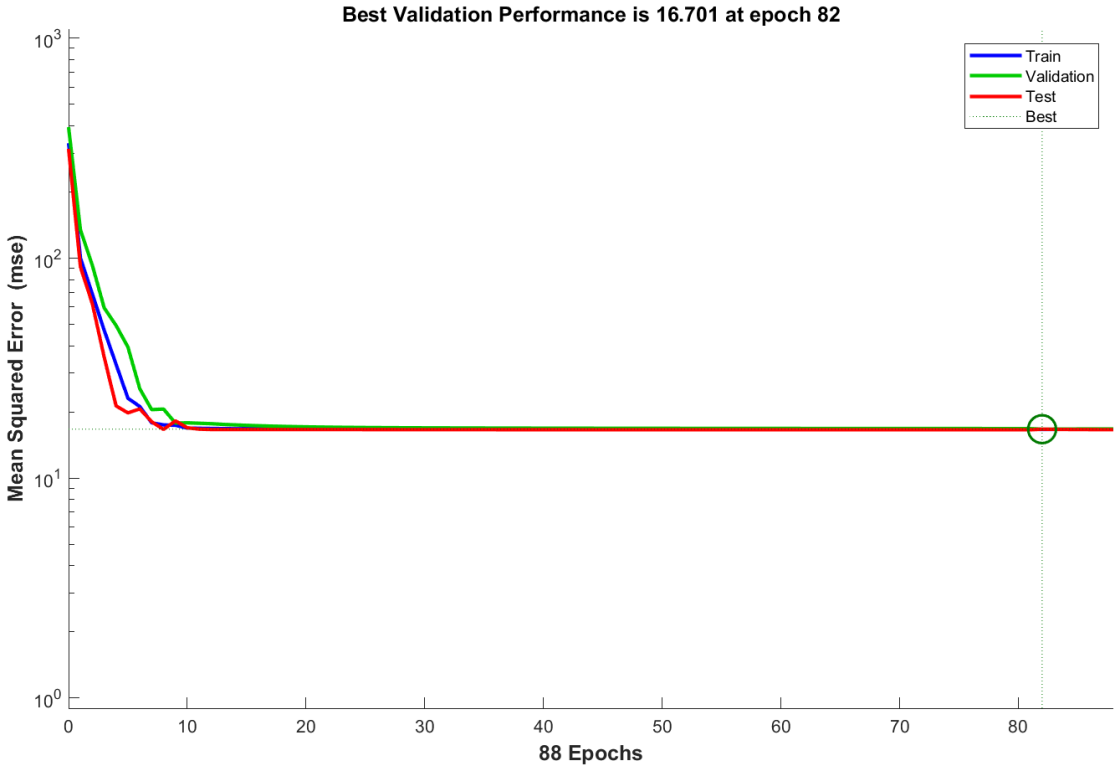


Figure 5.6.9 Performance (Mean squared error) for each of the epochs or train, validation, and test.

The Figure above shows that the neural network is improving. I

also show that the best version of the neural network was found on epoch 82.

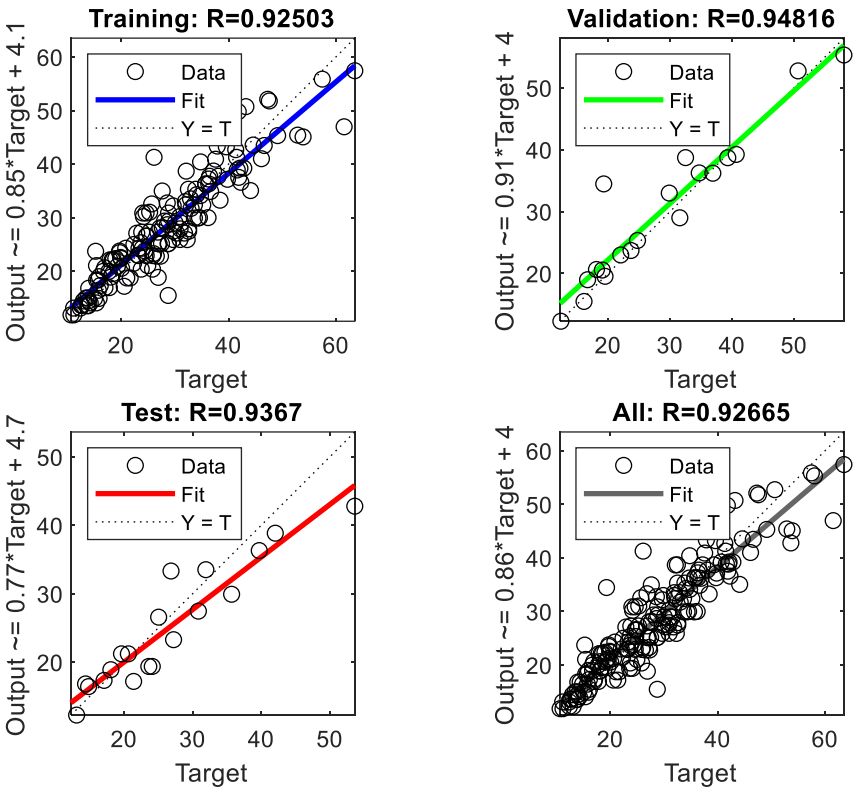


Figure 5.6.10 Charts showing the correlation between the target and the output.

The Figure above shows that the neural network is predicting well. Moreover, it demonstrates that there is much alignment between the output of the neural network and the target value.

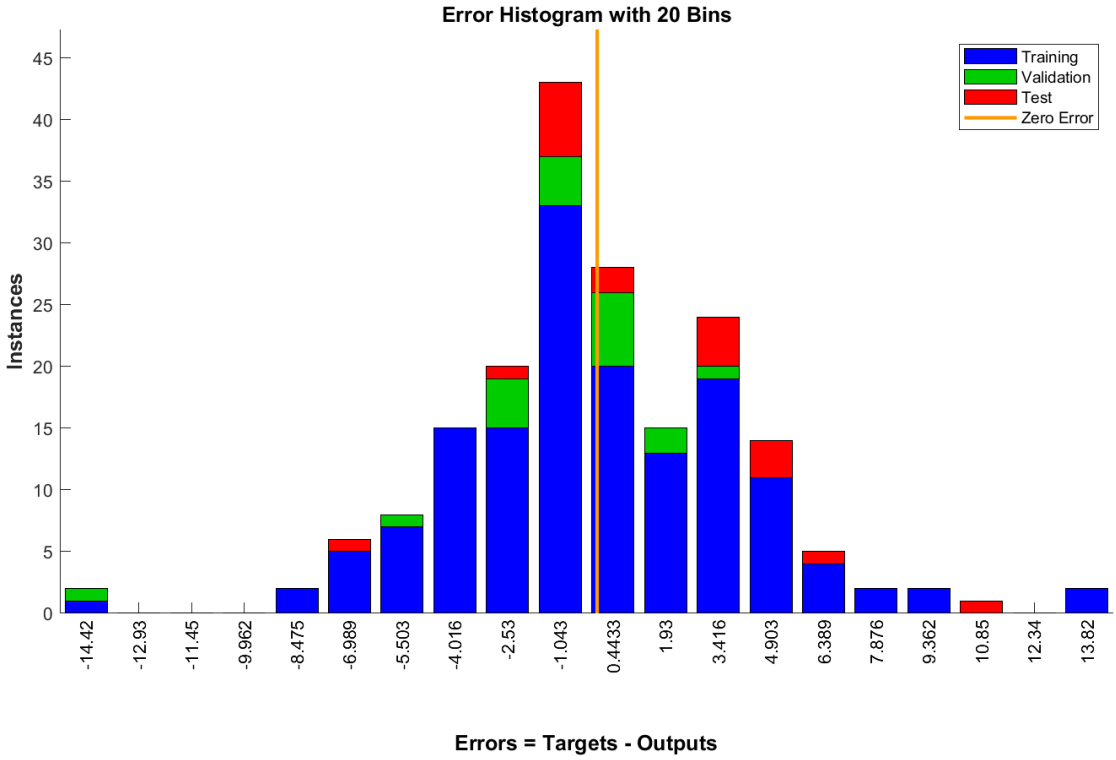


Figure 5.6.11 Error histogram of the neural network.

The error histogram mostly follows the curve expected from the neural network, namely that except for outliers, the errors follow the normal distribution. Nevertheless, the outliers show the blind spots of the model.

5.6.3.1 Comparison between predicted values vs real values

The comparison of predicted values vs real values is used to see to what extent the predictions will align with the real data. The

comparison is as follows:

Table 5.6-6 Comparison between real and predicted values when the neural network is applied to the original dataset.

Compressive Strength (Source)	Compressive Strength (Predicted)
17.92155855	22.13
18.3254812	22.13
18.54422754	22.13
20.8558458	24.29
23.32262387	24.29
23.9292315	24.29
24.65347537	26.58
24.77819508	26.58
25.05006746	26.58
30.07010786	29.00
31.18801294	29.00
31.5817028	29.00
23.26824437	22.91
24.66417555	22.91
25.89965488	22.91
26.92654678	25.12
27.0824143	25.12
28.75111365	25.12
29.68631878	27.46
30.84157217	27.46
32.57445226	27.46
33.64413133	29.92
34.30733235	29.92
35.68263401	29.92
24.02605286	30.86
24.64292245	30.86
28.82976209	30.86
31.93005181	33.52
32.91842391	33.52
35.76234635	36.31
36.31706604	36.31

39.7150431	36.31
40.67657424	39.24
42.12350638	39.24
42.8434002	39.24
44.59	43.56
52.88	45.41
57.46	55.86
28.59	32.75
34.1	34.31
39.59	43.22
15.25	23.73
22.38	25.00
35.2	32.39
47.3033537	52.10
32.50580381	38.72
37.90490985	43.37
44.10388345	35.06
36.9050754	36.20
25.30699576	31.01
41.90424766	37.52
29.70626735	32.19
19.30798905	34.47
22.90739308	27.10
32.30583692	25.90
26.90673088	18.85
19.30798905	20.92
19.70792283	23.48
23.70726064	23.71
22.30749241	21.46
19.70792283	23.77
41.81	49.79
58.04	55.32
43.24	50.73
37.59	40.91
46.65	43.47
53.89	45.08
46.13	41.01
39.81	37.16

26.85	33.32
36.31	37.22
32.12	38.69
27.65	34.98
25.69	32.56
33.03	31.74
23.83	27.30
19.91	22.57
47.6	51.79
63.52	57.43
50.65	52.74
41.34	42.69
49.15	45.32
61.53	46.97
53.64	42.79
42.05	38.85
36.67	34.89
41.63	38.90
34.8	40.41
42.3	36.60
34.78	34.11
38.42	33.26
28.6	28.69
24.4	23.81
16.67408745	19.98
19.08407654	20.55
30.29733684	27.12
36.48917792	37.73
17.73729623	19.98
20.08714893	20.55
31.80401899	27.12
38.08091366	37.73
15.42997543	18.36
18.08353808	18.90
27.51842752	25.16
32.53071253	35.31
13.95577396	16.82
16.11793612	17.34

26.04422604	23.29
29.87714988	32.99
15.72481572	18.36
18.08353808	18.90
28.7960688	25.16
33.90663391	35.31
14.39465479	16.82
17.08939061	17.34
27.22693625	23.29
31.96262869	32.99
12.95510303	14.45
15.06037891	14.92
23.74888792	20.38
28.08480194	29.36
13.93592784	14.45
15.89423096	14.92
25.83911346	20.38
28.86736346	29.36
11.13628718	13.12
13.66187707	13.56
21.05146811	18.75
25.26478927	27.30
10.66221347	11.85
12.39728002	12.27
20.57691384	17.19
23.68422317	25.33
12.40136479	13.12
13.89927435	13.56
21.68388678	18.75
26.84607622	27.30
11.20086269	11.85
13.09100365	12.27
21.40176799	17.19
24.75357757	25.33
19.00752454	22.38
22.04656081	22.99
34.59229666	30.01
26.12922092	41.27

19.98563305	22.38
23.09298341	22.99
36.19115808	30.01
41.50767557	41.27
16.9375	20.64
19.63282967	21.22
30.98008242	27.91
37.2103022	38.71
15.9375	18.99
18.43282967	19.54
29.68035714	25.92
34.71057692	36.25
18.1375	20.64
20.63255495	21.22
32.58008242	27.91
39.31057692	38.71
16.70655199	18.99
19.51466629	19.54
30.97222706	25.92
35.7525599	36.25
14.83978931	16.43
16.98687872	16.94
26.55697493	22.81
32.04692985	32.40
15.75112086	16.43
17.8075247	16.94
27.33256875	22.81
33.65120781	32.40
13.46266875	14.99
28.76499645	15.47
15.41032044	21.05
24.15249252	30.20
12.54481036	13.63
14.24440116	14.08
23.61437592	19.38
27.22875185	28.10
13.80041575	14.99
16.12780923	15.47

24.9596674	21.05
30.90614337	30.20
12.69039095	13.63
15.39102456	14.08
24.11875839	19.38
27.66379635	28.10

It could be seen that there are some differences between the real value and the predicted value.

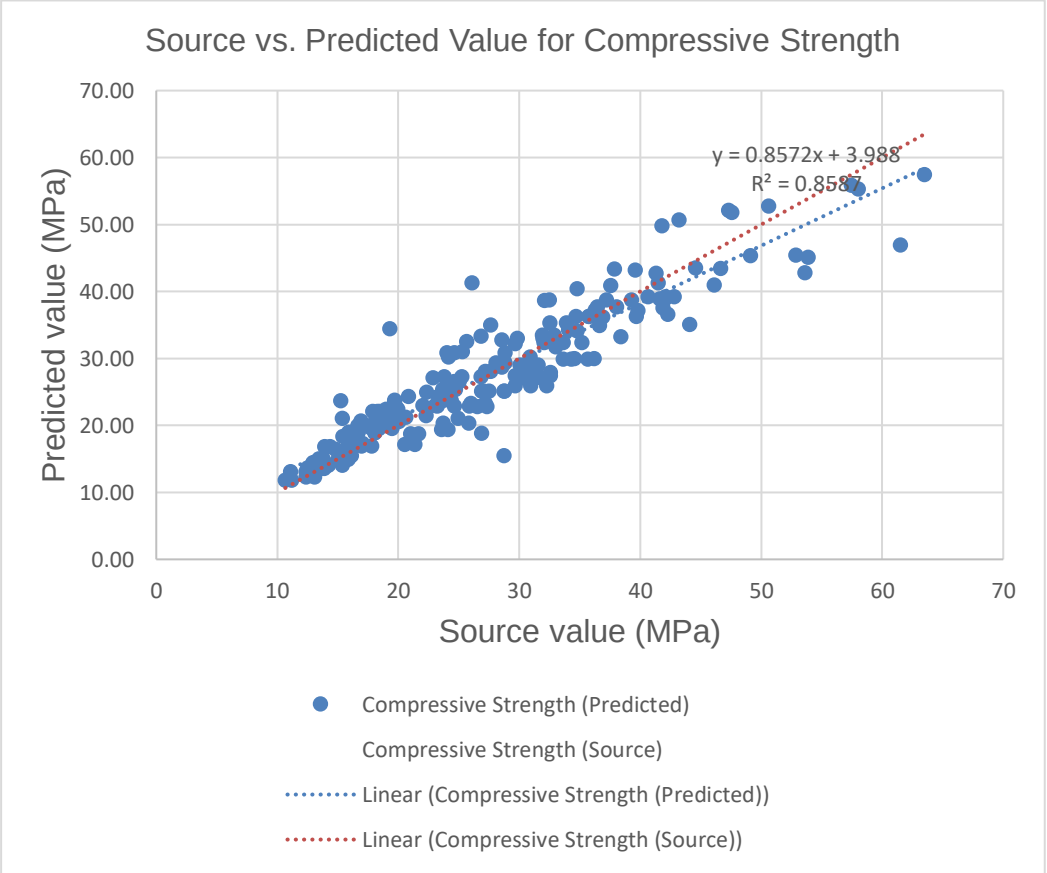


Figure 5.6.12 Source vs. Predicted Value for Compressive Strength

The chart would confirm the extent of similarity between the source value and the predicted value. The comparison between the y=x

trendline also highlights the difference between the real and predicted values. The graph also shows the areas where the outliers are.

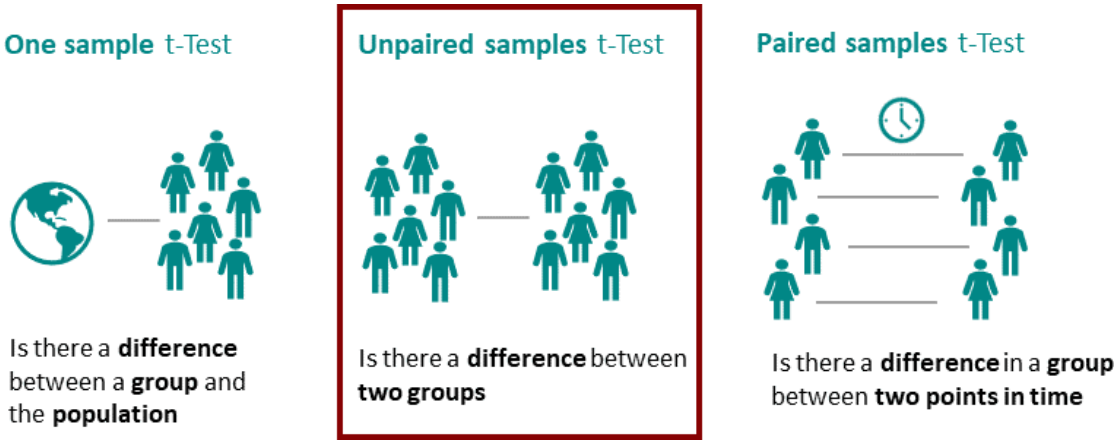


Figure 5.6.13 Different kinds of t-test (DATAtab Team, 2022)

From the figure above it can be seen that an unpaired samples t-test would be the t-test that would be most appropriate when looking at the difference between two groups. We are eager to see the difference between the real values and the values from the model to determine if the model is sufficiently similar.

Table 5.6-7 Comparison between real and predicted values when the neural network is applied to the original dataset.

	Compressive Strength (Source)	*Compressive Strength (Predicted)*
Mean	28.1145082	28.08636995
Variance	118.609677	101.4856381
Observations	189	189
Hypothesized Mean Difference	0	
df	374	

t Stat	0.026074896	
P(T<=t) one-tail	0.489605754	
t Critical one-tail	1.648938048	
P(T<=t) two-tail	0.979211507	
t Critical two-tail	1.966327183	

From the table above, the P(T<=t) is greater than 0.05 for both one-tail and two-tail. This would indicate that the predictions are sufficiently similar with the real values. The predictions, however, are only sufficiently accurate for the 10-42 MPa range. This could be seen as the values above 42 MPa are scarce.

5.6.3.2 Tweaked neural network code

```
function [Y,Xf,Af] = DTNNetImp2(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 19-Jul-2022 18:29:40.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = 21xQ matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number
of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 2 3 4 6 7 8 12 13 14 17 21];
x1_step2.xoffset =
[134.6;0;362.5;0;96.9;0.33;1565.35;0;0;0;0;3];
```

```
x1_step2.gain =
[0.00534188034188034;0.00202429149797571;0.00253936008125952;0.
00202429149797571;0.0137835975189524;9.09090909090909;0.0024019
6961508437;0.248138957816377;0.0192492781520693;0.0057920648711
2656;2;0.0377358490566038];
x1_step2.ymin = -1;

% Layer 1
b1 = 2.302140765828768032;
IW1_1 = [-0.31533317935786236985 2.2508091525668518784
1.1481664070351866869 2.2843975706989354535
0.87196893897494165415 -0.33551562597463419069 -
1.3430977212752601702 0.033147344578491416689 -
0.11872370855297048609 0.33073310313458315068
0.023387019977093425477 -0.15083317021764827692];

% Layer 2
b2 = 2.651195416278698147;
LW2_1 = -4.3640756352169178811;

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0378373770662546;
y1_step1.xoffset = 10.6622134653275;

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
    X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},2); % samples/series
else
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);
```

```
% Time loop
for ts=1:TS

    % Input 1
    temp = removeconstantrows_apply(X{1,ts},x1_step1);
    Xp1 = mapminmax_apply(temp,x1_step2);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Remove Constants Input Processing Function
function y = removeconstantrows_apply(x,settings)
y = x(settings.keep,:);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
```

```
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

5.7 Summary of the mean squared error of different analysis techniques

The tables would give that there are differences once the prediction has been stripped of the factors that are deemed unimportant. The lower MSE of the NDT test might be caused by higher amount of data and the regularity of the data.

Table 5.7-1 Breakdown of different regression techniques

Predictive model	R-Squared	Mean Squared Error
Non-destructive factors		
Linear Regression	0.95	7.4013
Stepwise Quadratic Regression with Interactions	0.94	8.8826
Exponential Gaussian Process Regression	0.96	4.9318
Untweaked neural network	0.93	9.3106
Tweaked neural network	0.986	4.6667
Destructive factors		
Linear Regression	0.83	20.86
Rational Quadratic Gaussian Process Regression	0.89	13.598
Tweaked neural network	0.9523	10.9439
Important NDT factors only		
Linear Regression	0.95	7.5425
Stepwise Quadratic Regression with Interactions	0.95	6.7388
Tweaked neural network	0.9788	6.1599

Important DT factors only		
Linear Regression	0.81	22.159
Matern 5/2 Gaussian Process Regression	0.88	14.703
Tweaked neural network	0.925	16.701

Table 5.7-2 Comparison between including all factors and including only important factors.

Predictive model	R-Squared	Mean Squared Error
Non-destructive factors		
All factors (Tweaked neural network)	0.986	4.6667
Important Factors (Tweaked neural network)	0.9788	6.1599
Destructive factors		
All Factors (Tweaked neural network)	0.9523	10.9439
Important Factors (Tweaked neural network)	0.925	16.701

5.8 Discussion

Linear regression has successfully been used as a sanity check. The most successful non-NN algorithm, stepwise quadratic regression with interactions was also featured. The repeatability of the results is also a matter of interest since the neural network also changes rapidly even without changing the neural network parameters.

The neural network, when tweaked, was also able to give a performance better than the other methods. The tweaking is concerned

with the changing of the size of the hidden layer. The hidden layer is modified so that the difference between the mean squared error (MSE) of the test set and the validation set would be small while obtaining a model with a MSE on the validation set lower than the best model tested.

The generic All – Train all available model types was used. The Train all option uses different models which could be categorized as: linear regression models, regression trees, support vector machines, gaussian process regression models, ensembles of trees and neural networks.

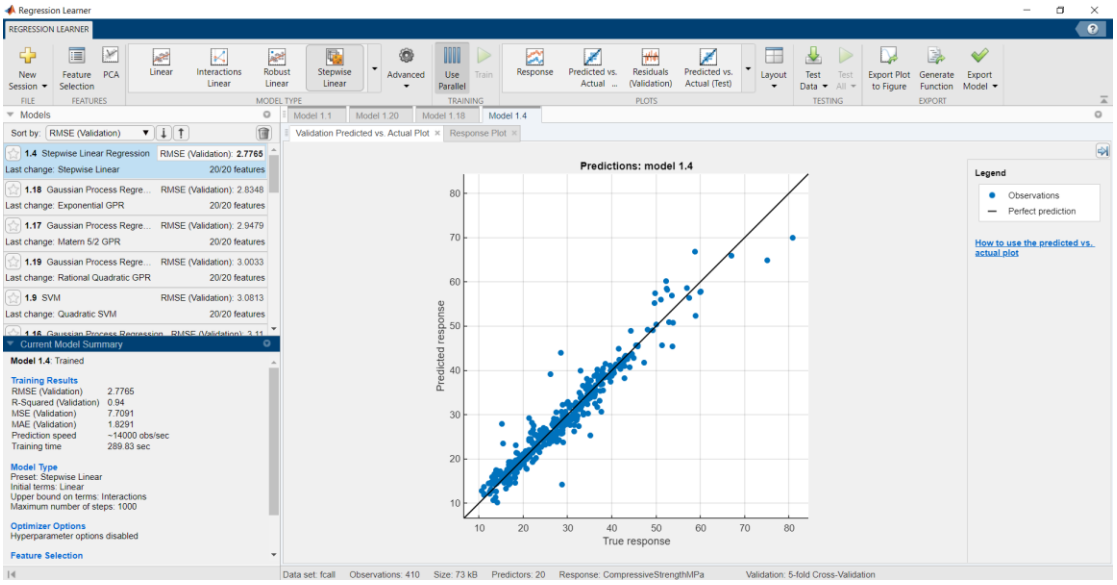


Figure 5.8.1 Different Models are used in the analysis.

The models are made to run (using parallel to make the analysis run faster) then afterwards, the models are ranked based on the root mean squared error (RMSE) in the validation set. The RMSE is used

since it measures how accurate the model would be.

Primary Component Analysis (PCA) could be added by choosing the PCA icon under regression learner then choosing the advanced PCA options. The default option of filtering by variance explained is sufficient since the simplified model would be desired when performing PCA analysis.

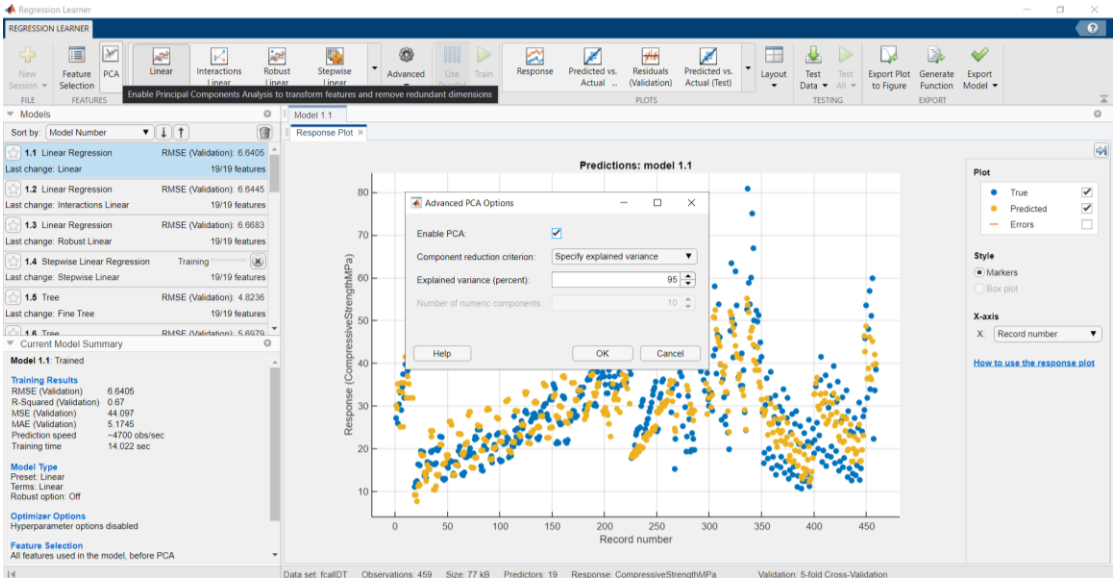


Figure 5.8.2 Figure to show the activation of PCA functionality

The PCA variables could be seen by first exporting the model. Now that the model is in the workspace, type the name of the model dot PCACoefficents. The Coefficients would be written in such a way such that the first row would contain the first feature and so on and so forth. The columns would denote each different primary component (PC). The first column would contain PC1 and so on and so forth.

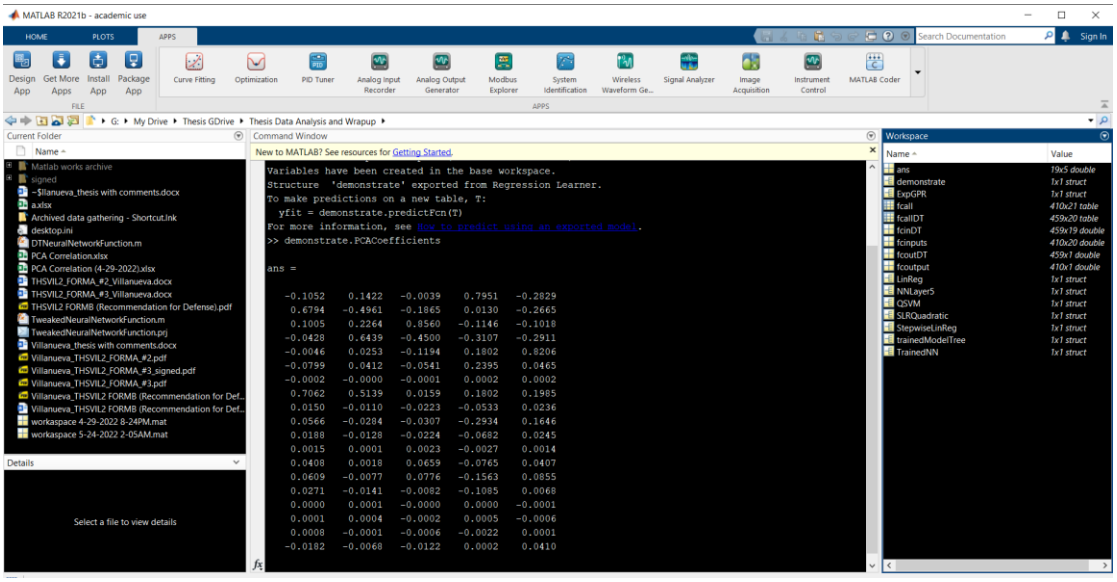


Figure 5.8.3 Figure to show the PCA coefficients

The analysis that was done was augmented using the Neural Network Fitting tool in MATLAB. One thing that is peculiar is that the MSE varies widely between each iteration. Except for when the hidden layer is either very small or very big (which in this case would be if the layer is 2 or less or 6 or more respectively), the values oscillate so widely and unpredictably that there is an impression that the modeling would have been both a trial-and-error process and an exercise in selection bias.

Using the PCA analysis alone would have excluded the age of concrete and the non-destructive tests to be part of the important factors, and thus, the linear regression result has been included with

regards to finding the important factors. An alternative approach would be to use the factors that PCA would find important and add the NDT tests and age of concrete. One more alternative approach would be to simply use the factors found by PCA to be important.

The NDT tweaked NN model with reduced factors was deemed to be the best model given that the factors have been reduced and out of the candidates, the MSE is acceptable and is better than the DT only counterpart.

Chapter VI

Conclusions and Recommendations

6.1 Conclusion

It was demonstrated that neural networks could give results better than other methods could. This could be demonstrated based on the R-squared value of the tweaked neural network. Nevertheless, the investigation also made known that more data would be appreciated, especially outside of the 10-45MPa range. This is since high strength concrete is used in some applications such as in skyscrapers. (*High-Strength Concrete*, n.d.) High strength concrete is used in those applications to minimize costs that would be needed if more columns are necessitated to carry the load. (*High Strength Concrete — What, Why, & How? – Nevada Ready Mix*, n.d.)

The non-negligible loss that would be created by using PCA could also be a sign that more data would be desired for the factors that were less commonly encountered. This is important since there are relatively few data that uses these factors when compared to data that uses the traditional factors such as cement, fine aggregate and coarse aggregate added and water to binder ratio.

With consideration to the model that would be chosen, the important values as determined through data with NDT would be used.

The important parameters for NDT are as follows: cement, fine aggregates, coarse aggregates, coarse RCA, fine RCA, water content, total unit weight, granite fines, fly ash content, ground granulated blast furnace slag, filler, crumb rubber, metakaolin content, content superplasticizer %, rebound number, and UPV.

The research was able to compare results from destructive methods with non-destructive methods. It was found that it is possible to create a reliable model even if the non-destructive methods were excluded. This is due to correlations such as the rebound number proportionally increasing with the age of the concrete.

Models using the factors to be considered have been created. Models using linear regression, stepwise quadratic regression with interactions, untweaked neural network and tweaked neural network have been created.

A model for the compressive strength of concrete from non-destructive test using machine learning has been obtained. The model is a neural network that contains only the more influential variables. This model could be seen on subsection 5.5.3.2 (page 157). This model (tweak neural network) is the best due to the higher R-squared compared to the other models. The best model contains 21 inputs with a hidden layer of size 1 to produce 1 output. This model has an R-

squared of 0.9773.

6.2 Recommendations

More data is recommended to be gathered. The analysis could be augmented if there is more data. An acquisition of more date would be appreciated to cover better the factors, other than the commonly understood factors (cement, coarse and fine natural aggregates, course and fine recycled aggregates, water content, total unit weight, and fly ash content).

It should be noted that the model would have an ideal amount of sample if $20p < m$, where p is the number of predictors and m is the limiting sample size. Given that the compressive strength is a continuous function, m would be equal to the sample size used. For the work cited, it would be acceptable even if just $10p < m$ is satisfied for "average" values. This would state that we could concede with only satisfying the equation $10p < m$, but the criteria of $20p < m$ would ideally be satisfied too (Harrell , 2015).

Better methods to include missing data, especially those missing NDT test results not included in the study should be analyzed. Missing out entire results that include NDT factors not considered should be mitigated if possible since we might be locked out of various combinations such as how Leeb hardness correlates with UPV. Treating

the NDT test results as zero for the missing data would simply introduce undue inaccuracies since unlike the less important additions to concrete (such as nano silica content), it would be wrong to say that the missing NDT variables would be zero. Stating that variables zero would be wrong since it would create a discontinuity; the behavior of the variable would not be as expected when taking into consideration the values needed to bring about a non-zero result from the other observations.

It would help if more of the factors are existent on both datasets. There are 7 factors (excluding NDT factors) that are zeroed out in the dataset that contains only destructive testing factors. More data would allow a better splitting of data without compromising too much the other dataset. This better splitting would allow a better analysis with regards to the factors and thus, more of the factors could be included. The splitting was not made to have more of the factors since it would have violated the minimum amount of data points in the model. (Harrell , 2015)

The only non-destructive factor that was used in the analysis are rebound number and ultrasonic pulse velocity. Other factors should be added to the analysis to have a better view of the situation.

Point load test could also be used to find the compressive strength of a concrete. Point load test is a cheaper way to test the compressive strength of concrete. However, its results would need to be

correlated with destructive compressive strength tests to get the result and the test is only destructive and not non-destructive. (Kazemi et al., 2020) (Franklin, 1985)

Other factors such as Leeb hardness could be used but would still need a greater foray into the current research to get the data needed. Leeb Hardness could be used as an alternative to Schmidt Rebound Number, considering that Leeb Hardness was able to demonstrate better results. Schmidt rebound hammer provides an information on material hardness from deeper surface layer, while Leeb rebound number seems to be informative of very thin surface layer of concrete. (Kovler et al., 2018).

Electrical resistivity might be usable with regards to determining the compressive strength. However, there would need to be more experiments testing the correlation between compressive strength and electrical resistivity. Electrical resistivity is currently used to test the resistance of concrete to corrosion. (Singh & Singh, 2018)

The electrical resistivity test used is the Wenner Array Four Probe method. The fact that Four copper probes/strips of size $10\,mm \times 50\,mm \times 2\,mm$ were embedded in the cubes at the time of casting to find the electrical resistivity means that it still needs further exploration as to how to make the concrete rebars be a sufficient alternative to the copper strips used when it comes to measuring the electrical resistivity,

lest the method would not be practical for use in the field from the undue added cost that would be need to use electrical resistivity if using four copper strips would still need to be applied to the elements. (Singh & Singh, 2018) Given the scale of civil engineering projects, even the small additions of thin strips would add up to a big cost.

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APPENDIX A

Raw Data Legends

The Legend for raw data of NDT would be as follows:

Table 0-1 Legend of the raw data. The symbol on the left corresponds to the factor on the right.

Symbol	Factor
A	Cement (kg/m^3)
B	Coarse aggregates (kg/m^3)
C	Fine aggregates (kg/m^3)
D	Coarse RCA (kg/m^3)
E	Fine RCA (kg/m^3)
F	Water content (kg/m^3)
G	Water to binder ratio
H	Total Unit Weight (kg/m^3)
I	Granite Fines (kg/m^3)
J	Fly ash content (kg/m^3)
K	Ground Granulated Blast Furnace Slag (GGBS) (kg/m^3)
L	Nano Silica (kg/m^3)
M	Filler (kg/m^3)
N	Crumb Rubber (kg/m^3)
O	Metakaolinite Content (kg/m^3)
P	polypropylene fibre (% by volume)
Q	dry curing
R	Superplasticizer (%)
S	(Schmidt) Rebound number
T	UPV (km/s)
U	Age of concrete (days)
V	Compressive strength (MPa)

The symbol on the left corresponds to the factor on the right in the raw data tables. A correspond to Cement (kg/m^3), B corresponds to Coarse aggregates (kg/m^3) and so on and so forth. It has been done this way since the factor would not fit.

APPENDIX B

Raw Data

Table 0-1 NDT raw data

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
0	1200	650	0	0	48	0.12	2298	0	0	0	0	0	0	400	0	0	3.5	27.10	3.25	28	27.3
0	1200	650	0	0	60	0.12	2410	0	0	0	0	0	0	500	0	0	3.5	30.2	3.37	28	29.5
0	1200	650	0	0	42	0.12	2242	0	0	0	0	0	0	350	0	0	3.5	25.6	3.19	28	25.9
0	1200	650	0	0	48	0.12	2298	0	0	0	0	0	0	400	0	0	3.5	30.8	3.41	28	30.4
0	1200	650	0	0	60	0.12	2410	0	0	0	0	0	0	500	0	0	3.5	31.9	3.53	28	33.2
0	1200	650	0	0	42	0.12	2242	0	0	0	0	0	0	350	0	0	3.5	28.1	3.3	28	29.1
0	1200	650	0	0	48	0.12	2298	0	0	0	0	0	0	400	0	0	3.5	33.7	3.58	28	34.5
0	1200	650	0	0	60	0.12	2410	0	0	0	0	0	0	500	0	0	3.5	35.8	3.69	28	37.4
0	1200	650	0	0	42	0.12	2242	0	0	0	0	0	0	350	0	0	3.5	31.5	3.49	28	32
0	1200	650	0	0	40	0.1	2290	0	400	0	0	0	0	0	0	0	2.5	29.5	3.81	28	39.8
0	1200	650	0	0	50	0.1	2400	0	500	0	0	0	0	0	0	0	2.5	32.2	3.89	28	41.7
0	1200	650	0	0	35	0.1	2235	0	350	0	0	0	0	0	0	0	2.5	28.2	3.7	28	38.3
0	1200	650	0	0	40	0.1	2290	0	400	0	0	0	0	0	0	0	2.5	33.2	3.92	28	42.9
0	1200	650	0	0	50	0.1	2400	0	500	0	0	0	0	0	0	0	2.5	35.6	3.99	28	45.5
0	1200	650	0	0	35	0.1	2235	0	350	0	0	0	0	0	0	0	2.5	30.6	3.83	28	40.5
0	1200	650	0	0	40	0.1	2290	0	400	0	0	0	0	0	0	0	2.5	36.2	4.03	28	45.9

0	1200	650	0	0	50	0.1	2400	0	500	0	0	0	0	0	0	0	2.5	38.5	4.11	28	49.3
0	1200	650	0	0	35	0.1	2235	0	350	0	0	0	0	0	0	0	2.5	33.9	3.93	28	43.1
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	14	3.55	7	11.1
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	20	3.39	7	12.2
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	17	3.49	7	12.4
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	18	4.05	28	16.4
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	19	4.03	28	16.2
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	18	4.02	28	16
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	21	4.23	90	19.5
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	21	4.23	90	18.7
273	0	936	0	0	216	0.79	1425	0	0	0	0	0	0	0	0	0	0	20	4.29	90	19.2
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	15	3.55	7	13.7
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	14	3.58	7	14.1
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	14	3.37	7	13.3
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	18	4.1	28	16.9
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	19	4.11	28	16.7
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	20	4.16	28	16.7
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	21	4.41	90	19.3
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	21	4.39	90	19.3
244	497	478	0	0	193	0.79	1412	0	0	0	0	0	0	0	0	0	0	20	4.39	90	19.7
291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	21	3.7	7	16.3
291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	21	3.87	7	16.4
291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	19	3.71	7	16.7

291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	22	4.17	28	20
291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	22	4.19	28	19.6
291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	22	4.18	28	20.1
291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	23	4.35	90	22.8
291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	22	4.43	90	20.9
291	0	927	0	0	215	0.74	1433	0	0	0	0	0	0	0	0	0	0	23	4.37	90	22.7
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	3.76	7	13
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	3.73	7	12.8
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	3.77	7	13
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	4.12	28	16
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	4.12	28	16.6
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	4.13	28	15.6
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	4.35	90	16.8
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	4.39	90	17.2
261	493	473	0	0	193	0.74	1420	0	0	0	0	0	0	0	0	0	0	18	4.35	90	17
313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	19	3.79	7	13.9
313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	18	3.75	7	14.2
313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	19	3.68	7	13.8
313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	15	3.96	28	17
313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	15	3.93	28	16.7
313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	14	3.95	28	16
313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	19	4.23	90	19.4
313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	21	4.23	90	20.5

313	0	915	0	0	216	0.69	1444	0	0	0	0	0	0	0	0	0	0	20	4.22	90	18.7
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	19	3.88	7	14.1
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	18	3.86	7	13.8
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	18	3.87	7	14.5
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	15	4.08	28	18.1
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	16	4.09	28	18
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	16	4.02	28	18.2
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	18	4.45	90	18.5
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	18	4.34	90	19.4
280	487	469	0	0	193	0.69	1429	0	0	0	0	0	0	0	0	0	0	18	4.39	90	20.1
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	21	3.93	7	18.5
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	21	3.95	7	18.5
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	22	3.94	7	19
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	20	4.09	28	22.1
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	21	4.09	28	22.9
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	21	4.11	28	22.5
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	24	4.45	90	24.5
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	25	4.48	90	24.8
332	0	920	0	0	216	0.65	1468	0	0	0	0	0	0	0	0	0	0	24	4.5	90	24.5
297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	19	3.84	7	16
297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	19	3.92	7	15
297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	19	3.91	7	14.9
297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	20	4.16	28	20.7

297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	20	4.14	28	20.1
297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	21	4.14	28	19.8
297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	23	4.42	90	22.5
297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	24	4.34	90	22.7
297	529	509	0	0	193	0.65	1528	0	0	0	0	0	0	0	0	0	0	23	4.41	90	23.1
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	18	3.93	7	17.6
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	18	3.93	7	18.2
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	19	3.93	7	16.8
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	21	4.09	28	20.2
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	20	4.18	28	21
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	21	4.09	28	19.8
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	24	4.35	90	23.2
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	23	4.51	90	23.5
354	0	909	0	0	216	0.61	1479	0	0	0	0	0	0	0	0	0	0	23	4.37	90	23.7
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	20	4.02	7	17.4
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	21	4.01	7	17
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	20	4.03	7	17.2
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	22	4.12	28	21.3
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	22	4.25	28	21.1
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	21	4.1	28	21.5
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	24	4.44	90	21.4
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	25	4.62	90	22.7
316	524	504	0	0	193	0.61	1537	0	0	0	0	0	0	0	0	0	0	27	4.52	90	22.3

372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	19	3.9	7	18.1
372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	19	3.96	7	18.4
372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	21	4	7	18.4
372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	20	4.13	28	20.8
372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	20	4.1	28	20.5
372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	24	4.43	28	27.6
372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	23	4.43	90	24.3
372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	24	4.47	90	22.9
372	0	905	0	0	216	0.58	1493	0	0	0	0	0	0	0	0	0	0	24	4.39	90	24.7
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	23	4.17	7	21.3
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	25	4.23	7	22.1
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	25	4.29	7	22.1
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	26	4.39	28	26.6
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	27	4.41	28	24.7
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	27	4.42	28	25.5
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	25	4.62	90	28.7
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	25	4.62	90	28.9
332	530	490	0	0	193	0.58	1545	0	0	0	0	0	0	0	0	0	0	25	4.62	90	28.3
400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	22	4.09	7	23
400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	22	4.13	7	22.9
400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	22	4.12	7	23.2
400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	25	4.26	28	26.4
400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	27	4.25	28	27.1

400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	28	4.24	28	28.1
400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	27	4.54	90	28.3
400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	27	4.48	90	27.4
400	0	890	0	0	216	0.54	1506	0	0	0	0	0	0	0	0	0	0	27	4.51	90	27.6
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	23	4.23	7	22.5
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	22	4.2	7	22.2
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	23	4.23	7	22.9
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	25	4.39	28	28.6
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	24	4.4	28	28
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	24	4.43	28	27.6
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	28	4.53	90	29.9
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	28	4.51	90	30.5
357	528	488	0	0	193	0.54	1566	0	0	0	0	0	0	0	0	0	0	26	4.55	90	30.6
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	24	4.21	7	28.1
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	26	4.18	7	27.4
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	26	4.23	7	26.8
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	24	4.28	28	31.6
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	27	4.32	28	32.2
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	26	4.28	28	31.5
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	32	4.65	90	35.1
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	32	4.62	90	34.8
432	0	935	0	0	216	0.5	1583	0	0	0	0	0	0	0	0	0	0	32	4.61	90	34.1
386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	23	4.17	7	21.3

386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	23	4.18	7	21.7
386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	23	4.12	7	21.3
386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	24	4.31	28	26.2
386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	23	4.32	28	25.8
386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	24	4.32	28	25.8
386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	28	4.66	90	32.4
386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	27	4.66	90	32.2
386	550	469	0	0	193	0.5	1598	0	0	0	0	0	0	0	0	0	0	29	4.7	90	31.7
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	22	4.02	7	21.8
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	25	4.08	7	21.3
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	24	4.07	7	22
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	25	4.24	28	28.3
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	25	4.23	28	27.6
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	24	4.17	28	26.5
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	25	4.65	90	28.4
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	28	4.59	90	29
480	0	908	0	0	216	0.45	1604	0	0	0	0	0	0	0	0	0	0	27	4.67	90	28.9
429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	25	4.25	7	27.3
429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	26	4.19	7	27.4
429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	25	4.08	7	27.8
429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	28	4.45	28	33.6
429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	30	4.37	28	32.1
429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	30	4.45	28	34.4

429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	34	4.78	90	34.1
429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	32	4.73	90	32.7
429	533	412	0	0	193	0.45	1567	0	0	0	0	0	0	0	0	0	0	35	4.66	90	34.4
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	23	4.18	7	29.1
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	24	4.17	7	30.2
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	25	4.17	7	28.9
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	29	4.38	28	36.1
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	28	4.31	28	36.7
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	29	4.31	28	36.2
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	34	4.68	90	37.8
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	35	4.69	90	37.2
514	0	884	0	0	216	0.42	1614	0	0	0	0	0	0	0	0	0	0	34	4.85	90	38
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	25	4.36	7	30.2
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	25	4.32	7	30.6
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	25	4.32	7	30.1
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	32	4.42	28	38
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	32	4.39	28	34.6
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	31	4.52	28	36.3
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	35	4.82	90	36.6
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	36	4.9	90	36.8
460	558	419	0	0	193	0.42	1630	0	0	0	0	0	0	0	0	0	0	36	4.72	90	37.8
301	652	0	0	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	32.99	4.46	28	39.9
301	489	0	163	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	32	4.33	28	37

301	326	0	326	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	32	4.28	28	35
301	163	0	489	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	29.98	4.18	28	33
301	0	0	652	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	30.02	4.16	28	33
301	652	410	0	410	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	32.99	4.33	28	38.5
301	652	0	0	820	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	32	4.29	28	37
301	0	410	652	410	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	29.98	4.1	28	35.2
301	0	0	652	820	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	26.98	3.91	28	34.5
301	652	0	0	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	34.02	4.61	56	42.5
301	489	0	163	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	32	4.48	56	40
301	326	0	326	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	32	4.36	56	37
301	163	0	489	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	31.01	4.4	56	34.9
301	0	0	652	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	30.02	4.31	56	34
301	652	410	0	410	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	34.02	4.48	56	40
301	652	0	0	820	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	32.99	4.37	56	38
301	0	410	652	410	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	32	4.26	56	37.5
301	0	0	652	820	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	27.97	4.15	56	34.9
301	652	0	0	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	34.02	4.62	90	43.5
301	489	0	163	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	32.99	4.52	90	41.9
301	326	0	326	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	32.99	4.4	90	40
301	163	0	489	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	32	4.34	90	35.3
301	0	0	652	0	277	0.78	1286	0	55.5	0	0	0	0	0	0	0	0	30.02	4.32	90	35.6
301	652	410	0	410	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	34.02	4.48	90	42.8
301	652	0	0	820	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	34.02	4.4	90	41

301	0	410	652	410	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	32	4.32	90	38.8
301	0	0	652	820	277	0.78	2106	0	55.5	0	0	0	0	0	0	0	0	29.02	4.21	90	37.5
269	832	1148	0	0	98.2	0.37	2373	0	0	0	0	104	0	0	0	0	0	40.7	5.1	28	52.3
135	833	1150	0	0	96.9	0.41	2351	0	103	0	0	104	0	0	0	0	0	30.48	4.89	28	47.3
135	833	1150	0	0	96.9	0.41	2375	0	103	0	2.4	104	0	0	0	0	0	38.74	5.01	28	58.9
135	833	1150	0	0	96.9	0.41	2347	0	103	0	4.7	104	0	0	0	0	0	45.43	5	28	49.7
135	833	1150	0	0	96.9	0.41	2358	0	103	0	7.1	104	0	0	0	0	0	32.65	4.66	28	43.9
135	833	1035	0	0	96.9	0.41	2281	0	103	0	0	104	115	0	0	0	0	25.69	4.69	28	38.1
135	833	1035	0	0	96.9	0.41	2316	0	103	0	2.4	104	115	0	0	0	0	28.52	4.91	28	53.7
135	833	1035	0	0	96.9	0.41	2298	0	103	0	4.7	104	115	0	0	0	0	33.52	4.77	28	44.3
135	833	1035	0	0	96.9	0.41	2315	0	103	0	7.1	104	115	0	0	0	0	21.56	4.62	28	36.1
135	833	920	0	0	96.9	0.41	2226	0	103	0	0	104	230	0	0	0	0	19.6	4.4	28	33.5
135	833	920	0	0	96.9	0.41	2226	0	103	0	2.4	104	230	0	0	0	0	23.52	4.39	28	42.9
135	833	920	0	0	96.9	0.41	2190	0	103	0	4.7	104	230	0	0	0	0	27.65	4.44	28	37.7
135	833	920	0	0	96.9	0.41	2209	0	103	0	7.1	104	230	0	0	0	0	19.6	3.96	28	31.5
135	833	805	0	0	96.9	0.41	2171	0	103	0	0	104	345	0	0	0	0	15.69	3.25	28	30.1
135	833	805	0	0	96.9	0.41	2178	0	103	0	2.4	104	345	0	0	0	0	22.65	3.4	28	32.9
135	833	805	0	0	96.9	0.41	2171	0	103	0	4.7	104	345	0	0	0	0	18.52	3.24	28	33.1
135	833	805	0	0	96.9	0.41	2190	0	103	0	7.1	104	345	0	0	0	0	14.6	2.94	28	28.9
269	832	1148	0	0	98.2	0.37	2372	0	0	0	0	104	0	0	0	0	0	40.91	5.09	28	52.6
269	832	1148	0	0	98.2	0.37	2398	0	0	0	2.69	104	0	0	0	0	0	51.96	5.24	28	80.9
269	832	1148	0	0	98.2	0.37	2389	0	0	0	5.37	104	0	0	0	0	0	44	5.05	28	58.9
269	832	1148	0	0	98.2	0.37	2359	0	0	0	8.06	104	0	0	0	0	0	35.92	5.01	28	53.9

269	832	1033	0	0	98.2	0.37	2313	0	0	0	0	104	115	0	0	0	0	44.95	5.15	28	60.1
269	832	1033	0	0	98.2	0.37	2326	0	0	0	2.69	104	115	0	0	0	0	48.99	5.18	28	75.1
269	832	1033	0	0	98.2	0.37	2317	0	0	0	5.37	104	115	0	0	0	0	46.97	5.02	28	67
269	832	1033	0	0	98.2	0.37	2308	0	0	0	8.06	104	115	0	0	0	0	32.95	4.76	28	50.1
269	832	918	0	0	98.2	0.37	2235	0	0	0	0	104	230	0	0	0	0	27.96	4.77	28	44
269	832	918	0	0	98.2	0.37	2259	0	0	0	2.69	104	230	0	0	0	0	37.94	4.92	28	52.4
269	832	918	0	0	98.2	0.37	2272	0	0	0	5.37	104	230	0	0	0	0	30.93	4.7	28	49.9
269	832	918	0	0	98.2	0.37	2263	0	0	0	8.06	104	230	0	0	0	0	25.94	4.74	28	51.3
269	832	804	0	0	98.2	0.37	2196	0	0	0	0	104	345	0	0	0	0	22.86	4.16	28	40.4
269	832	804	0	0	98.2	0.37	2199	0	0	0	2.69	104	345	0	0	0	0	26.9	4.31	28	45
269	832	804	0	0	98.2	0.37	2184	0	0	0	5.37	104	345	0	0	0	0	19.89	3.81	28	41.6
269	832	804	0	0	98.2	0.37	2165	0	0	0	8.06	104	345	0	0	0	0	21.91	3.51	28	28.5
0	1290	549	0	0	92.5	0.23	2341	0	205	205	0	0	0	0	0	0	2.86	30.07	3.06	7	29.1
0	1290	549	0	0	92.5	0.23	2341	0	205	205	0	0	0	0	0	0	2.86	42.26	3.25	28	45.9
0	1290	549	0	0	92.5	0.23	2341	0	205	205	0	0	0	0	0	0	2.86	44.19	3.66	90	53.5
0	1290	439	0	0	92.5	0.23	2341	110	205	205	0	0	0	0	0	0	2.86	32.15	3.12	7	32
0	1290	439	0	0	92.5	0.23	2341	110	205	205	0	0	0	0	0	0	2.86	44.22	3.44	28	48.1
0	1290	439	0	0	92.5	0.23	2341	110	205	205	0	0	0	0	0	0	2.86	46.26	4.12	90	57
0	1290	329	0	0	92.5	0.23	2341	220	205	205	0	0	0	0	0	0	2.86	32.96	3.21	7	34
0	1290	329	0	0	92.5	0.23	2341	220	205	205	0	0	0	0	0	0	2.86	46.44	3.51	28	51.1
0	1290	329	0	0	92.5	0.23	2341	220	205	205	0	0	0	0	0	0	2.86	47.07	4.36	90	59.9
0	1290	220	0	0	92.5	0.23	2341	329	205	205	0	0	0	0	0	0	2.86	25.26	3.04	7	22.4
0	1290	220	0	0	92.5	0.23	2341	329	205	205	0	0	0	0	0	0	2.86	29.15	3.2	28	33.6

0	1290	220	0	0	92.5	0.23	2341	329	205	205	0	0	0	0	0	0	2.86	31.74	3.45	90	38.6

Table 0-2 Destructive tests only raw data

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	7	17.9
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	7	18.3
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	7	18.5
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	14	20.9
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	14	23.3
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	14	23.9
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	21	24.7
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	21	24.8
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	21	25.1
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	28	30.1
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	28	31.2
207	830	415	0	0	114	0.55	1565	0	0	0	0	0	0	0	0	0	0	0	0	28	31.6
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	7	23.3
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	7	24.7
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	7	25.9
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	14	26.9
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	14	27.1
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	14	28.8

264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	21	29.7
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	21	30.8
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	21	32.6
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	28	33.6
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	28	34.3
264	790	395	0	0	132	0.5	1580	0	0	0	0	0	0	0	0	0	0	0	0	28	35.7
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	7	24
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	7	24.6
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	7	28.8
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	14	31.9
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	14	32.9
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	21	35.8
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	21	36.3
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	21	39.7
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	28	40.7
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	28	42.1
363	725	363	0	0	163	0.45	1613	0	0	0	0	0	0	0	0	0	0	0	0	28	42.8
509	858	796	0	0	176	0.33	2339	0	0	0	0	0	0	0	0	0	1.2	0	0	3	44.6
509	858	796	0	0	176	0.33	2339	0	0	0	0	0	0	0	0	0	1.2	0	0	7	52.9
509	858	796	0	0	176	0.33	2339	0	0	0	0	0	0	0	0	0	1.2	0	0	28	57.5
475	858	769	0	0	197	0.4	2299	0	0	0	0	0	0	0	0	0	0.8	0	0	3	28.6
475	858	769	0	0	197	0.4	2299	0	0	0	0	0	0	0	0	0	0.8	0	0	7	34.1
475	858	769	0	0	197	0.4	2299	0	0	0	0	0	0	0	0	0	0.8	0	0	28	39.6

452	858	694	0	0	233	0.5	2237	0	0	0	0	0	0	0	0	0	0	0	0	3	15.3
452	858	694	0	0	233	0.5	2237	0	0	0	0	0	0	0	0	0	0	0	0	7	22.4
452	858	694	0	0	233	0.5	2237	0	0	0	0	0	0	0	0	0	0	0	0	28	35.2
269	832	1148	0	0	98.2	0.37	2373	0	0	0	0	104	0	0	0	0	0	0	0	7	47.3
135	833	1150	0	0	96.9	0.41	2351	0	103	0	0	104	0	0	0	0	0	0	0	7	32.5
135	833	1150	0	0	96.9	0.41	2375	0	103	0	2.4	104	0	0	0	0	0	0	0	7	37.9
135	833	1150	0	0	96.9	0.41	2347	0	103	0	4.7	104	0	0	0	0	0	0	0	7	44.1
135	833	1150	0	0	96.9	0.41	2358	0	103	0	7.1	104	0	0	0	0	0	0	0	7	36.9
135	833	1035	0	0	96.9	0.41	2281	0	103	0	0	104	115	0	0	0	0	0	0	7	25.3
135	833	1035	0	0	96.9	0.41	2316	0	103	0	2.4	104	115	0	0	0	0	0	0	7	41.9
135	833	1035	0	0	96.9	0.41	2298	0	103	0	4.7	104	115	0	0	0	0	0	0	7	29.7
135	833	1035	0	0	96.9	0.41	2315	0	103	0	7.1	104	115	0	0	0	0	0	0	7	19.3
135	833	920	0	0	96.9	0.41	2226	0	103	0	0	104	230	0	0	0	0	0	0	7	22.9
135	833	920	0	0	96.9	0.41	2226	0	103	0	2.4	104	230	0	0	0	0	0	0	7	32.3
135	833	920	0	0	96.9	0.41	2190	0	103	0	4.7	104	230	0	0	0	0	0	0	7	26.9
135	833	920	0	0	96.9	0.41	2209	0	103	0	7.1	104	230	0	0	0	0	0	0	7	19.3
135	833	805	0	0	96.9	0.41	2171	0	103	0	0	104	345	0	0	0	0	0	0	7	19.7
135	833	805	0	0	96.9	0.41	2178	0	103	0	2.4	104	345	0	0	0	0	0	0	7	23.7
135	833	805	0	0	96.9	0.41	2171	0	103	0	4.7	104	345	0	0	0	0	0	0	7	22.3
135	833	805	0	0	96.9	0.41	2190	0	103	0	7.1	104	345	0	0	0	0	0	0	7	19.7
269	832	1148	0	0	98.2	0.37	2372	0	0	0	0	104	0	0	0	0	0	0	0	3	41.8
269	832	1148	0	0	98.2	0.37	2398	0	0	0	2.69	104	0	0	0	0	0	0	0	3	58
269	832	1148	0	0	98.2	0.37	2389	0	0	0	5.37	104	0	0	0	0	0	0	0	3	43.2

269	832	1148	0	0	98.2	0.37	2359	0	0	0	8.06	104	0	0	0	0	0	0	0	3	37.6
269	832	1033	0	0	98.2	0.37	2313	0	0	0	0	104	115	0	0	0	0	0	0	3	46.7
269	832	1033	0	0	98.2	0.37	2326	0	0	0	2.69	104	115	0	0	0	0	0	0	3	53.9
269	832	1033	0	0	98.2	0.37	2317	0	0	0	5.37	104	115	0	0	0	0	0	0	3	46.1
269	832	1033	0	0	98.2	0.37	2308	0	0	0	8.06	104	115	0	0	0	0	0	0	3	39.8
269	832	918	0	0	98.2	0.37	2235	0	0	0	0	104	230	0	0	0	0	0	0	3	26.9
269	832	918	0	0	98.2	0.37	2259	0	0	0	2.69	104	230	0	0	0	0	0	0	3	36.3
269	832	918	0	0	98.2	0.37	2272	0	0	0	5.37	104	230	0	0	0	0	0	0	3	32.1
269	832	918	0	0	98.2	0.37	2263	0	0	0	8.06	104	230	0	0	0	0	0	0	3	27.7
269	832	804	0	0	98.2	0.37	2196	0	0	0	0	104	345	0	0	0	0	0	0	3	25.7
269	832	804	0	0	98.2	0.37	2199	0	0	0	2.69	104	345	0	0	0	0	0	0	3	33
269	832	804	0	0	98.2	0.37	2184	0	0	0	5.37	104	345	0	0	0	0	0	0	3	23.8
269	832	804	0	0	98.2	0.37	2165	0	0	0	8.06	104	345	0	0	0	0	0	0	3	19.9
269	832	1148	0	0	98.2	0.37	2372	0	0	0	0	104	0	0	0	0	0	0	0	7	47.6
269	832	1148	0	0	98.2	0.37	2398	0	0	0	2.69	104	0	0	0	0	0	0	0	7	63.5
269	832	1148	0	0	98.2	0.37	2389	0	0	0	5.37	104	0	0	0	0	0	0	0	7	50.7
269	832	1148	0	0	98.2	0.37	2359	0	0	0	8.06	104	0	0	0	0	0	0	0	7	41.3
269	832	1033	0	0	98.2	0.37	2313	0	0	0	0	104	115	0	0	0	0	0	0	7	49.2
269	832	1033	0	0	98.2	0.37	2326	0	0	0	2.69	104	115	0	0	0	0	0	0	7	61.5
269	832	1033	0	0	98.2	0.37	2317	0	0	0	5.37	104	115	0	0	0	0	0	0	7	53.6
269	832	1033	0	0	98.2	0.37	2308	0	0	0	8.06	104	115	0	0	0	0	0	0	7	42.1
269	832	918	0	0	98.2	0.37	2235	0	0	0	0	104	230	0	0	0	0	0	0	7	36.7
269	832	918	0	0	98.2	0.37	2259	0	0	0	2.69	104	230	0	0	0	0	0	0	7	41.6

269	832	918	0	0	98.2	0.37	2272	0	0	0	5.37	104	230	0	0	0	0	0	0	7	34.8
269	832	918	0	0	98.2	0.37	2263	0	0	0	8.06	104	230	0	0	0	0	0	0	7	42.3
269	832	804	0	0	98.2	0.37	2196	0	0	0	0	104	345	0	0	0	0	0	0	7	34.8
269	832	804	0	0	98.2	0.37	2199	0	0	0	2.69	104	345	0	0	0	0	0	0	7	38.4
269	832	804	0	0	98.2	0.37	2184	0	0	0	5.37	104	345	0	0	0	0	0	0	7	28.6
269	832	804	0	0	98.2	0.37	2165	0	0	0	8.06	104	345	0	0	0	0	0	0	7	24.4
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0	1	0.8	0	0	5	16.7
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0	1	0.8	0	0	7	19.1
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0	1	0.8	0	0	28	30.3
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0	1	0.8	0	0	56	36.5
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	5	17.7
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	7	20.1
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	28	31.8
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	56	38.1
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0	1	0.8	0	0	5	15.4
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0	1	0.8	0	0	7	18.1
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0	1	0.8	0	0	28	27.5
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0	1	0.8	0	0	56	32.5
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	5	14
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	7	16.1
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	28	26
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	56	29.9
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	5	15.7

440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	7	18.1
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	28	28.8
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	56	33.9
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	5	14.4
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	7	17.1
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	28	27.2
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	1	0.8	0	0	56	32
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0	1	0	0	0	5	13
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0	1	0	0	0	7	15.1
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0	1	0	0	0	28	23.7
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0	1	0	0	0	56	28.1
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	5	13.9
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	7	15.9
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	28	25.8
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	56	28.9
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0	1	0	0	0	5	11.1
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0	1	0	0	0	7	13.7
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0	1	0	0	0	28	21.1
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0	1	0	0	0	56	25.3
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	5	10.7
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	7	12.4
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	28	20.6
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	56	23.7

440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	5	12.4
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	7	13.9
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	28	21.7
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	56	26.8
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	5	11.2
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	7	13.1
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	28	21.4
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	1	0	0	0	56	24.8
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0	0	0.8	0	0	5	19
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0	0	0.8	0	0	7	22
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0	0	0.8	0	0	28	34.6
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0	0	0.8	0	0	56	26.1
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	5	20
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	7	23.1
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	28	36.2
440	988	692	0	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	56	41.5
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0	0	0.8	0	0	5	16.9
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0	0	0.8	0	0	7	19.6
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0	0	0.8	0	0	28	31
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0	0	0.8	0	0	56	37.2
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	5	15.9
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	7	18.4
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	28	29.7

440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	56	34.7
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	5	18.1
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	7	20.6
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	28	32.6
440	494	692	494	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	56	39.3
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	5	16.7
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	7	19.5
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	28	31
440	0	692	988	0	176	0.4	2296	0	0	0	0	0	0	0	0.1	0	0.8	0	0	56	35.8
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0	0	0	0	0	5	14.8
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0	0	0	0	0	7	17
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0	0	0	0	0	28	26.6
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0	0	0	0	0	56	32
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	5	15.8
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	7	17.8
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	28	27.3
440	988	692	0	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	56	33.7
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0	0	0	0	0	5	13.5
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0	0	0	0	0	7	28.8
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0	0	0	0	0	28	15.4
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0	0	0	0	0	56	24.2
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	5	12.5
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	7	14.2

440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	28	23.6
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	56	27.2
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	5	13.8
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	7	16.1
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	28	25
440	494	692	494	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	56	30.9
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	5	12.7
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	7	15.4
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	28	24.1
440	0	692	988	0	242	0.55	2362	0	0	0	0	0	0	0	0.1	0	0	0	0	56	27.7